THESIS REPORT

Minimizing water shortages and operational costs of a water supply system by providing decision support on real-time control

A case study in La Paz, Bolivia

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Preface

First, I would like to thank all the people who supported me during my master thesis and gave me the opportunity to perform my research about the drink water supply project in La Paz. The project introduced me to the subject of operational water management, which I experienced as very challenging. I learned a lot about the subject and especially improved my programming skills.

I owe many thanks to Harm Nomden, who came up with the project and offered me a spot as intern within Royal HaskoningDHV to execute my master thesis. He provided me with valuable feedback, and the extensive discussions we had did certainly contribute to the quality of my research. I would also like to give many thanks to Ric Huting, who helped me to explain my research in a more understandable way. Furthermore, I would like to say thanks to all the colleagues at the Rivers and Coasts department of Royal HaskoningDHV that I met and spoke to. They provided a nice atmosphere and work environment.

Finally, I need to say many thanks to Martijn Booij and Maarten Krol, my supervisors from the University of Twente. They helped me defining my research objective and scope. Besides, their critical view provided guidance and feedback to execute my research and write my report on an academic level.

Summary

The citizens of the La Paz – El Alto metropolis in Bolivia depend on a natural system of catchments for their drinking water. The water supply consists of different source regions which are connected to multiple water treatment plants (WTPs). This natural system is subject to an annual meteorological pattern with a wet season usually occurring from December until April, while the remainder of the year is dry. To provide the citizens with drinking water during the entire year reservoirs are constructed to store water, which are connected to the WTPs by pipelines and open channels.

In 2016 the La Paz – El Alto metropolis, experienced its worst drought in 25 years, which resulted in a water rationing period of two-months, affecting over 400.000 of its 1.6 million citizens. The drought problems are caused by a combination of climate variability and climate change, rapid urban expansion, extensive mining, agricultural and industrial activities, out-dated infrastructure and mediocre operational management. These different aspects have been studied, however the operational control of the infrastructure was not a subject of study. In 2018 some river intakes were built where water can be transported directly from a river to a WTP for additional supply. Using these intakes can mitigate or prevent water shortages but introduce additional operational costs. Furthermore, these intakes make the operational control of the water supply system more complex. Therefore, this thesis focuses on an optimal real-time control of the river intakes and provides decision support.

Since the behaviour of the natural water system determines the amount of water available to the supply system, it is important to understand the hydrological behaviour. Rainfall-runoff models are built to estimate the runoff based on precipitation data. Uncertainty in future precipitation can be addressed by introducing precipitation scenarios. The combination of a limited intake capacity and a variable potential intake discharge makes it preferable to plan and execute the control on the intakes far ahead in the future. To make such a proactive control possible, the precipitation scenarios need a time horizon of at least one year.

Besides the hydrological boundary conditions, an optimization approach is constructed that can determine the least costly operational control of the water supply system based on a given set of initial (hydrological) conditions and future discharges. The decision about which scenario to use depends on the desired trade-off between the water shortages and the operational costs. A conservative approach results in a guarantee of little water shortages but high operational costs, while a risky approach results in more probable water shortages but low operational costs.

In the future water shortages and operational costs will both increase due to increasing population and consumption. Already in 2022 there will be shortages at the WTPs when using the intakes in full potential. By 2027 the water supply system will not suffice to reliably satisfy the increased demands of the WTPs, potentially leading to relative shortages between 2% and 10%. Besides the growing water shortages, this also results in an increase in operational costs, potentially leading to an increase of up to 0.04 €/m^2 for the consumer by 2027.

To use the decision support the decision maker should consider to what extent water shortages are acceptable and what budget is available for using the intakes. Ultimately the decisions regarding the operational control of the intakes is about the balance between the risk of having a water shortage in the future and the costs of lowering this risk. When the decision-maker has determined the preferred balance, the decision support on real-time control will provide advice on a strategic level of how much water to take in and how to distribute it over to the different WTPs.

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1 Introduction

The introduction of this thesis report is structured as follows; first the water shortage problems in La Paz are described and then the current state of knowledge is presented. This state of the art identifies a research gap which is described and finally the research objective and research questions are formulated.

1.1 Motivation

One of the most basic human needs is drinking water. Shortages on domestic drinking water supplies can disrupt communities and even whole cities. Recent water shortages in the La Paz – El Alto urban area, the main metropolis of Bolivia has led to political tensions and economic damage (Luttikhuis, 2016). In 2016 the city experienced its worst drought in 25 years, which resulted in a two-month water rationing period, affecting over 400.000 of its 1.6 million citizens. During this period trucks had to transport water over long distances towards collection points, where citizens often had to wait for hours in order to fill some canisters (Martínez, 2017). There are several reasons explaining the La Paz drought problems; rapid urban expansion, climate variability and climate change, extensive mining, agricultural and industrial activities, out-dated infrastructure and mediocre operational management.

1.1.1 Demographic pressure

The rapid increasing urban population leads to a rise in domestic water demand. Between 2001 and 2012 the population of El Alto increased with at least 30% (Buxton et al., 2013). However not only the population increases, also the water use per capita is rising due to a more extensive household water consumption (Shi et al., 2013).

Buxton et al. (2013) estimated the effect of the future increase in personal water consumption. The average water use in El Alto was 52 litres per person per day in 2013 and they predict that this will become 77 litres by 2050. According to Shi et al. (2013) many households in El Alto are currently not connected to the water distribution network, while more households are getting connected in the future. They also argue that a household connection will increase the personal water demand due to e.g. the use of flush toilets. For wealthier areas in La Paz however, domestic consumption is estimated to rise from 222 to 227 litres per person per day. According to Buxton et al. (2013) the overall increase in water demand due to personal increase and population rise, is projected to be 20% to 40% by 2050.

Shi et al. (2013) investigated the relationship between demographic growth and climate change driven water shortages. They argue that there is a clear connection between natural hazards and periods of accelerated migration towards La Paz and El Alto. Droughts can lead to a decline in agricultural productivity, forcing people from rural areas to migrate to the urban area of La Paz – El Alto, while at the same time the urban water supply is most limited. This is also concluded by Calizaya et al. (2012), who investigated the historical growth patterns of La Paz and El Alto between 1976 and 2012. Furthermore, they calculated that the population of El Alto grew with an annual average of 3.7% since 2001. They also indicate that the population of La Paz and El Alto is projected to grow from around 1.6 million in 2012 to 3 million in 2050.

1.1.2 Climate variability and climate change

Climate variability and climate change poses a threat to the city's water supply with changing precipitation patterns and rising temperatures leading to changing stream flow regimes. The hydrology is characterized by a clear annual interaction between a wet and a dry season. Most precipitation occurs during the period December – March, while the remaining months are mostly dry. During these dry months, the city's water supply depends for a substantial part on glacial melt water (Cook et al., 2016). Increasing temperatures lead to shrinking glaciers, while this loss in melt water is not compensated by extra rainfall (Buxton et al., 2013).

A considerable amount of research has been dedicated to the effects of climate change on water availability in Bolivia. Shi et al. (2013) and Cook et al. (2016) investigated the effects of climate change on glaciers in the Andes and more specifically the effects on the water availability of La Paz and El Alto. They explain that the ice mass of the Bolivian glaciers decreased with 40% between 1986 and 2014 and that temperatures are projected to increase with 2 °C by 2050, leading to a further decline of glacial mass. The World bank (2008) estimated that around 30% to 60% of El Alto's water supply comes from glaciers, while Buxton et al. (2013) estimated this to be between 20% and 28% for La Paz and El Alto combined. This indicates that La Paz is less dependent on glacial melt than El Alto.

Buxton et al. (2013) state that there will also be a reduction of rainfall, since most climate models predict a decrease in precipitation, although model predictions are uncertain. Based on the IPCC climate scenarios, Shi et al. (2013) used a conceptual rainfall runoff model including snow and glacier accumulation/melt for predicting future stream flows. For the watersheds supplying El Alto, most climate scenarios lead to a decrease in stream flows of 20% to 40% by 2050, while other climate scenarios show a decrease of 6%. They also mention that El Niño and La Niña events have a substantial impact on the variations between years and seasons. Lordemann et al. (2009) made a comparison between El Niño and La Niña events leading to the conclusion that El Niño events lead to droughts, whereas La Niña events could lead to heavy rainfall and flooding, which might also result in landslides in the surrounding areas of La Paz.

1.1.3 Mining and industrial activities

Furthermore, mining and industrial activities put extra pressure on the local water availability. Mining activities have contaminated one of the sources of the water supply system leading to high treatment costs, while the industry increases the demand of the water supply system and generates high quantities of water contaminated with heavy metals, textile dyes and other waste (GAMEA, 2002). These contaminations pollute the city's major rivers affecting not only the city's liveability, but also the downstream agricultural supply system. According to Shi et al. (2013) there is a high potential for industrial wastewater reuse, however connecting the city's major industrial areas to existing wastewater treatment plants requires a lot of new pipelines. They explain that another approach would be to develop smaller industrial wastewater treatment plants within the industrial zones to purify the water locally and make it available for reuse.

There are also problems concerning mining activities, in particular at reservoir Milluni (see Figure 2), where the water is getting heavily contaminated by mining activities that were performed within this basin during the last century (EPSAS, 2014b). Currently the mining activities have stopped, however after a rainfall event runoff is carrying contaminated materials into the reservoir. Arsenic, cadmium and copper are examples of heavy metals that are present in the area.

1.1.4 Infrastructure

Other problems are caused by the aging of the system infrastructure, resulting into an overall leakage of about 35% (EPSAS, 2014a). Furthermore the current control and measuring system is not useful for real-time control and quick response to changing hydrological conditions (Nomden et al., 2017), resulting in water losses. The infrastructure is managed and operated by the local metropolitan water and sewage company, Empresa Pública de Água y Saneamiento (EPSAS). In 2012 they estimated water losses in El Alto to be around 35%, however they do not know how much of this percentage is due to leakage and how much is due to illegal connections (EPSAS, 2014c). During the 1980s water losses were as high as 50%, but with the help of U.S. engineers and international funding the EPSAS engineers managed to reduce this to the current 35%. The number from EPSAS is very comparable to the estimate of the World Bank (2006) on average water losses in developing countries. In comparison to the average water loss rate of 15% for developed countries, substantial gains are possible. Besides reducing water losses, Buxton et al. (2013) proposed solutions to enlarge the wastewater treatment capacity and add new supply sources to the system. Multiple upgrades and adjustments have been made to the supply system in the past years, which led to a focus on new infrastructure and potential new sources.

1.2 State of the art

As described in the motivation, the impact of different factors influencing the water shortage problems in La Paz – El Alto have already been examined. Currently EPSAS is involved in multiple studies, to investigate different aspects of the water supply of the system; the surveying of new water sources for future use, the impact of climate change, and the planning of new infrastructure (EPSAS, 2014a). These studies are all focused on the long-term reliability of the water supply system, with the current and proposed infrastructure configurations and forecasted water demand. However, little research is dedicated to the operational control of the local drinking water system. Therefore, EPSAS chose to cooperate with Royal HaskoningDHV in 2017 for a study to increase the efficiency of the water system operations.

From an international perspective multiple studies have been executed on the operational control of drink water systems. These studies can be divided in two categories; supply management and demand management (Butler & Memon, 2006). According to Sun et al. (2013) the supply management applies to the entire supply system including natural water sources, reservoirs and their corresponding connections to the water treatment. Whereas, the demand management applies to the distribution of water from the water treatment to the consumer. These categories can be operated at different time scales, due to different system dynamics.

Extensive research is already dedicated to the optimization of the demand side of water systems. Sun et al. (2016) & Ocampo-Martinez et al. (2009) applied Model Predictive Control (MPC) to the water distribution network of Barcelona, based on an operational time horizon of 24-hours. Their objective was to reduce costs associated with water losses. Similar studies were performed by Cembrano et al. (2000), Hata et al. (2015) and Leirens et al. (2014) optimizing the real-time operational control of water distribution networks within Portugal, Colombia and Japan respectively. These studies use 24-hour and 48-hour time horizons based on 30-minute and 60-minute intervals to minimize operational costs and guarantee the water supply. They include hydraulic effects inside the water networks and predict the future water demand based on statistics. Another research on real-time control of water networks is executed by Kang (2014) aiming to minimize operational costs by the optimal control of pumps under demand fluctuations and energy tariff variations.

Few studies are focused on the supply side of water systems. Sun et al. (2013) did investigate the operational control of the water supply system of Barcelona, which is operated on a 30-day time horizon using daily intervals. The optimization process is based on a mass-balance and focuses on minimizing the waste of water and conservation of ecological flows while satisfying the demand.

Other research regarding the supply of drinking water is more oriented towards optimal reservoir operation and management, often including other (conflicting) interests like flood control, hydropower and irrigation. For example Lund & Ferreira (1996), Labadie & Asce (2004) and Rani & Madalena (2010) studied multipurpose multi reservoir systems and present different approaches of multi-objective optimisation based on varying optimization methods. Schwanenberg et al. (2015) studied the effects of multi-objective optimisation of a large reservoir in Brazil on flood mitigation under hydrological forecast uncertainty. However, these studies do not specifically place the reservoir operation in the perspective of a drink water supply system and use relatively short time-horizons varying between a few weeks to a couple of months.

1.3 Research gap

The La Paz – El Alto case is not characterized as an integrated water problem, as it does not include other interests than the supply of drinking water. Besides, the involved time-horizon is an important aspect in controlling the La Paz – El Alto water supply, since the interannual variability in rainfall and runoff plays an important role on the short-term operational control. This makes it important to consider a long time-horizon to include these interannual effects. In contrast to the short-term operational control of valves and gates on e.g. an hourly basis, the interannual variability focuses more on a strategic level about how much water to take in during the coming month.

Currently there is a gap in knowledge between the daily supply operations and the long-term infrastructure planning. Operational control is now mainly performed based on experience from the technical experts of EPSAS and by a monthly analysis of the reservoirs water balance. Due to the increasing size and complexity of the entire system, a decision support system is strongly recommended by Nomden et al. (2017). This research seeks to address the research gap between daily operation and long-term infrastructure planning by studying the effects of long-term decision support on real-time operational control.

1.4 Research aim

The objective of this thesis is the following:

Provide long term decision support on real-time control for the water supply system of La Paz by establishing an appropriate optimization approach to adjust the operational control to possible future hydrological conditions.

This decision support will focus specifically on three operational control options of the water supply system; two river intakes, which allow the intake of extra water into the system at additional costs and a channel which can change the distribution of stored water among the two subsystems of Incachaca and Hampaturi. By providing the decision-maker with insight about the impact of current reservoir levels, hydrological conditions and precipitation scenarios on the future state of the water supply system, the trade-off between possible water shortages and added operational costs becomes clear. Due to the hydrological behaviour of the water system decisions should be made well in advance. Therefore, this decision support on 'real-time' control will focus on a long term, with a time horizon of two years. In this research the 'real-time' control is not studied in a live situation, but the 'real-time' control process is simulated over a 17-year period to study the effects of different control strategies on the water shortages and operational costs.

1.5 Research questions

To structure the research objective, the problem will be divided into two parts; the hydrological modelling and the decision support on 'real-time' control. Since the behaviour of the natural water system determines the amount of water available to the supply system, it is important to understand the hydrological behaviour. A rainfall-runoff model will be built for the different catchments to study the hydrological boundary conditions of the water supply system. This rainfall-runoff model will also be used to simulate the runoff based on precipitation scenarios. To handle the uncertainty in future precipitation, it is necessary to simulate future precipitation trajectories for the water supply system. These future trajectories can be simulated by introducing a collection of scenarios, used as a forecast ensemble to simulate the 'real-time' decision making process on a time horizon of two years. The following research question and sub-questions are dedicated to the hydrological analysis:

What are the hydrological boundary conditions for the water supply system?

1. *What is the variability of the rainfall and runoff and how can this be modelled in an appropriate way?*
2. *What are appropriate precipitation scenarios?*

Subsequently, this collection of scenarios will be used to simulate the water supply system for a variety of future precipitation conditions. The control of the water supply system will be optimized for each scenario individually to minimize the water shortages and operational costs. The resulting collection of optimal control actions will provide the decision-maker with different options to control the water supply system. It is important to study how different control strategies impact the trade-off between water shortage and operational costs on a long term. This is studied by executing a simulation of the 'real-time' control process over a 17-year period based on 2000 – 2016 data. The following research question and sub-questions are dedicated to the long-term simulation and decision support on 'real-time' control:

What are the advantages of 'real-time' decision support?

3. *What is a consistent method for choosing the real-time control actions?*
4. *How do the control strategies respond to different reservoir volumes?*
5. *How do the control strategies relate to the trade-off between water shortages and operational costs?*
6. *How does the trade-off between water shortage and operational costs change in the future?*

To gain insight in the relation between research questions and to structure the research, a flowchart is added, see Figure 1.

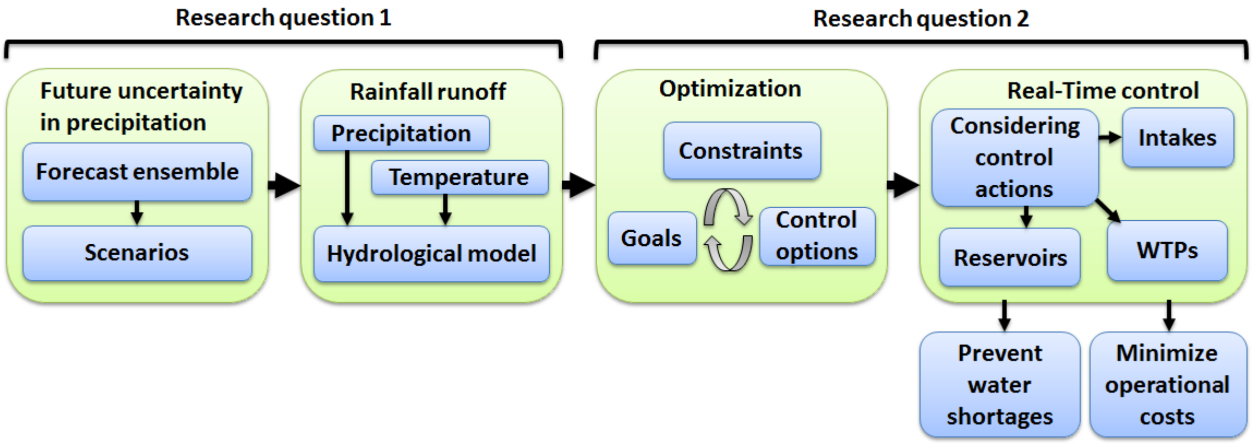

Figure 1: Flowchart of the research structure

Research question 1 applies to the precipitation uncertainty and its effect on the hydrological boundary conditions of the water supply system. The variability in precipitation is expressed by introducing a set of scenarios as a forecast ensemble. Subsequently, this set of scenarios is used as input for the hydrological model which calculates discharge scenarios. Research question 2 applies to the control of the water supply system and its effect on the trade-off between water shortages and operational costs. The resulting discharge scenarios are used during the optimization process to come up with the optimal control actions to satisfy the defined goals with the given constraints. During the 'real-time' control process the final control actions are chosen and implemented and their effects on the water supply system are calculated.

1.6 Outline

The remainder of the report is structured as follows; Chapter 2 describes the choices regarding the study area and correspondingly the available data. Furthermore, the choices regarding the used models and tools are explained. Chapter 3 presents all the methods which are used to produce the results. Chapter 4 is dedicated to the results. In chapter 5 the effects of decisions, assumptions and uncertainties on the results are discussed. And finally, in chapter 6 the research questions are answered and recommendations are presented.

2 Study area, data & tools

This chapter of the report is dedicated to the choice of the study area and correspondingly the available data. Furthermore, the choices regarding the models and tools that will be used within the methods chapter are explained.

2.1 Study area

The city of La Paz is situated along the Choqueyapu canyon at an elevation of approximately 3,650 meters above sea level (m+MSL). El Alto is the major suburb of La Paz and is situated at an altitude of 4,000 (m+MSL) on the plateau, northwest of La Paz. The municipalities of La Paz and El Alto have a combined population of 1.6 million inhabitants according to the National Population and Housing Census of 2012. The water supply system providing the entire urban area of La Paz and El Alto consists of seven source regions: Tuni, Milluni, Choqueyapu, Incachaca, Huayllara, Hampaturi and Palcoma, see Figure 2. These source regions are connected to a total of four water treatment plants (WTPs): El Alto, Achachicala, Chuquiaguillo and Pampahasi.

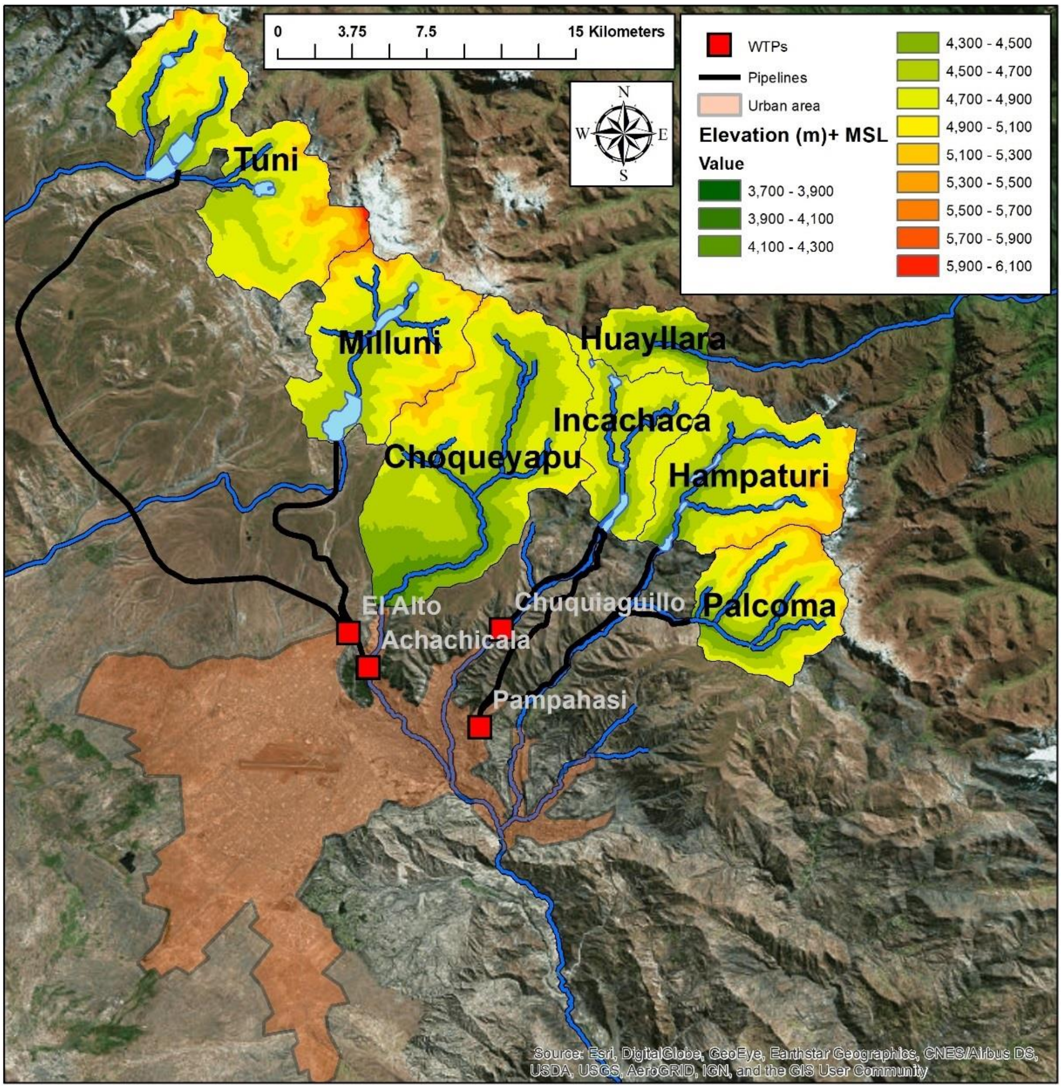

Figure 2: Overview of the source regions of the water supply system, divided according to the six sub-systems: Tuni, Milluni, Choqueyapu, Incachaca, Huayllara, Hampaturi and Palcoma

2.1.1 System scope

The infrastructure of the water supply system consists of reservoirs, river intakes and WTPs, which are interconnected by natural streams, pipelines or open channels. The connections between the reservoirs consist of natural streams, whereas the connections between the source regions and the WTPs consist of pipelines and open masonry channels. Some source regions are connected to multiple WTPs, which makes the operational control of the water supply system more flexible, but also more complex.

The reservoirs provide storage to the water supply system and are connected in a parallel or a serial configuration. The river intakes can provide the system with additional supply by taking water directly from a river and diverting it via a pipeline to a WTP or to a reservoir. Depending on the available river discharge, the intake discharge can be varied over time in order to control the flow in the pipeline. At the WTPs the water is purified and distributed to different parts of the La Paz – El Alto urban area, see Figure 3.

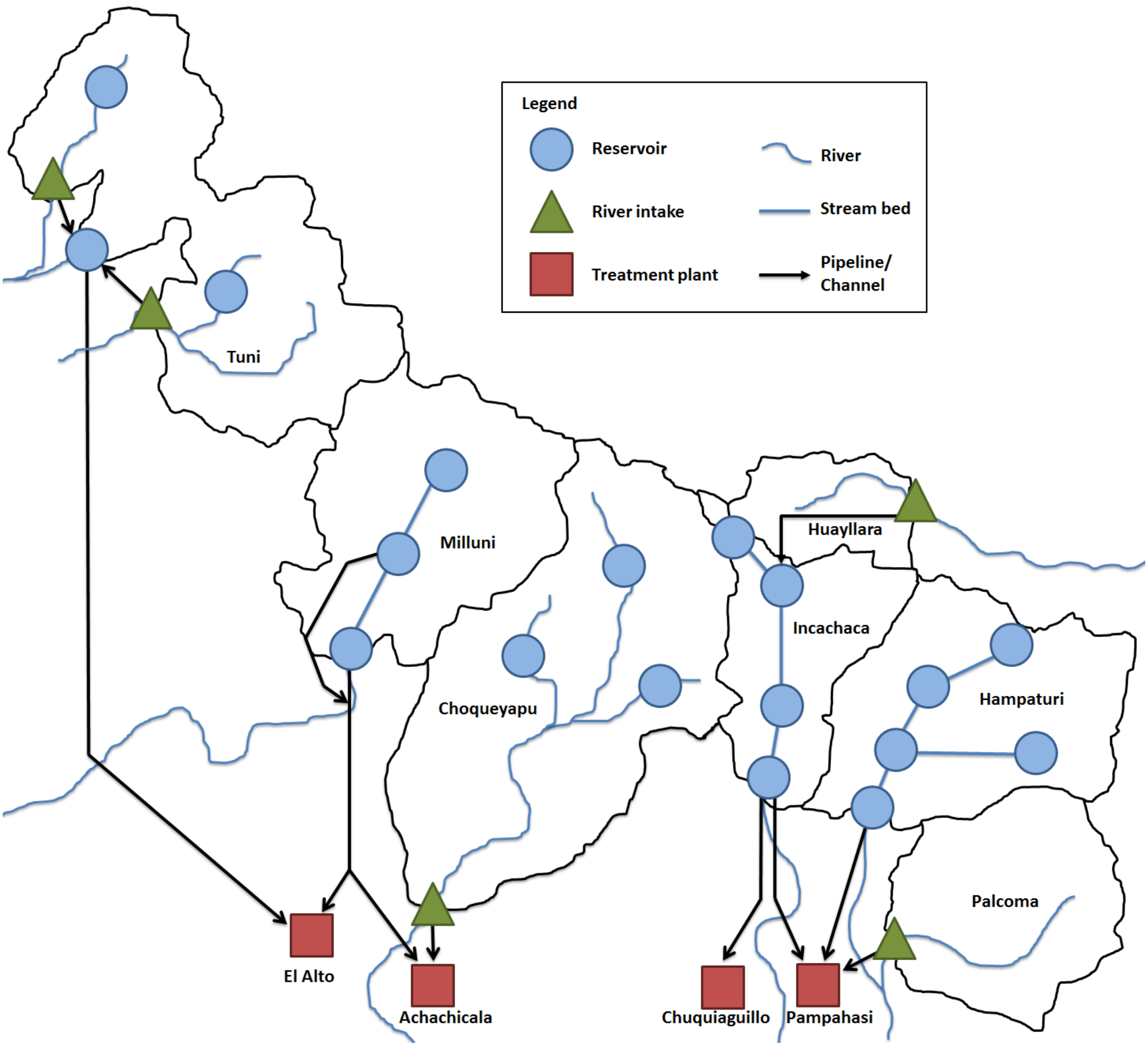

Figure 3: Schematization of the entire La Paz – El Alto water supply system

For this thesis, it is decided to limit the study area to the source regions Incachaca, Huayllara, Hampaturi, and Palcoma, because together these four catchments possess all the individual infrastructural components, connections and control options that are present in the overall supply system. This makes the optimization process of the 'real-time' control in this research interesting and realistic. Besides, these four catchments offer a better data availability. Furthermore, this decision is favourable for the feasibility of the research since studying the entire supply system takes a lot of time. These four catchments and their corresponding WTPs are described in more detail in section 2.1.3.

2.1.2 Natural characteristics

To get a better understanding of the water supply system, its functioning and operation, some important information regarding the natural characteristics is provided. First the climate is described, providing some information about precipitation, temperature and hydrological variability. Then the land cover of the study area is described.

2.1.2.1 Climate

The climate is dominated by the highlands and mountains ranging between 3700 and 6000 (m+MSL). It is characterized by highly seasonal rainfall patterns having short wet summers with rainfall of high intensity, followed by long, cold and dry winters with occasional snowfall. The raining season usually lasts from December to March, resulting in runoff during the period January – April. The hydrological year is defined as July – June. The average annual rainfall at La Paz is 600 mm, however this number can greatly increase with the altitude. At La Paz the average annual temperature is 11 ° C, while the average summer temperature is 17 ° C. Strong winds from the highlands are often attacking the area. Temperatures are projected to rise by as much as 2 ° C by 2050 (Shi et al., 2013).

The altitude range of the Incachaca system is roughly 4400 – 5100 (m+MSL), whereas the altitude range of both Hampaturi and Palcoma is roughly 4200 – 5500 (m+MSL). Temperature measurements are available for the Alto Achachicala station, located within the Choqueyapu basin (adjacent to Incachaca) at an altitude of 4383 (m+MSL), see Table 1. Furthermore, the temperature is measured in La Paz itself at altitudes of 3600 and 4000 (m+MSL).

Table 1: Monthly temperature at station Alto Achachicala averaged over the period 1999 - 2017

Month	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Average High (°C)	11.7	11.5	11.1	11.0	11.3	11.1	11.0	11.6	11.4	12.3	12.9	12.7
Average (°C)	5.8	5.7	5.0	4.0	2.5	1.2	0.7	2.0	3.0	4.4	5.2	5.9
Average Low (°C)	-0.1	-0.2	-1.2	-2.9	-6.3	-8.8	-9.6	-7.7	-5.4	-3.5	-2.5	-0.9

The precipitation data for the years 2000 – 2016 is monthly averaged to indicate the seasonal variability, see Table 2. The wet season lasts from December until March, with the rainfall amounts being considerably higher in comparison to the other months.

Table 2: Monthly rainfall at the stations Incachaca and Hampaturi averaged over the period 2000 - 2016

	Average rainfall (mm)											
System	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Incachaca	131	103	69	29	9.1	5.5	7.5	12	27	44	44	104
Hampaturi	124	101	67	25	10.0	6.0	9.5	11	29	46	47	103

The seasonal hydrological variability is shown in Table 3 by monthly averaging the streamflow data over the period 2005 – 2016.

Table 3: Monthly streamflows for the Incachaca, Hampaturi and Palcoma systems averaged over the period 2005 - 2016

Average streamflow (mm)			
Month	**Incachaca**	**Hampaturi**	**Palcoma**
JAN	51	95	84
FEB	69	111	95
MAR	37	58	54
APR	18	27	29
MAY	5	8	9
JUN	2	3	4
JUL	3	2	4
AUG	6	2	3
SEP	12	6	6
OCT	11	10	10
NOV	8	17	17
DEC	10	49	42
Total	231	389	357

Based on the average streamflow data it is clear that the hydrological response of Hampaturi and Palcoma is comparable, but the response of Incachaca is different, producing much less discharge while receiving a comparable amount of rainfall according to Table 2.

2.1.2.2 Land cover

Since the study area is located between 4200 and 5500 meters above sea level, the presence of trees and vegetation is scarce, the land is mostly covered by grass. The study area features natural storage in the form of glaciers and bofedals (EPSAS, 2014b). The Hampaturi basin has a glacial coverage of approximately 1%, which is mainly provided by the Serkhe Khota glacier, delivering its water to the Serkhe Khota reservoir (EPSAS, 2014b). This glacier contributes about 1.6% to the discharge of the basin. The Incachaca basin has no glacial coverage.

Bofedals are a type of wetland naturally occuring at high altitudes at depressions in the landscape (Fonkén, 2014), see Figure 4. They consist of peat and have water absorbing capabilities depending on the plants which formed the peat and the depth of its stratum. Bofedals can act like a natural sponge, impacting the evapotranspiration and runoff of the basin, by storing water from rainfall and snow and glacial melt during the wet season and releasing it during the dry season (Squeo & Warner, 2006).

Figure 4: A picture of a typical bofedal located in the Bolivian Andes

2.1.3 System description

In this section the three source regions Incachaca, Hampaturi and Palcoma and their corresponding WTPs will be described in more detail. An overview of basic information is given in Table 4 and Table 5.

Table 4: Information about surface area, storage capacity and average outflow

System	Surface area	Reservoir capacity	Average annual system outflow	
	km^2	hm^3	hm^3/year	l/s
Incachaca	34	6.55	7.86	249
Hampaturi	58	13.25	22.56	720
Palcoma	42	0	15.01	482

The surface area refers to the total drainage area of the source region, the reservoir capacity is the total storage capacity present within the source region by adding the capacities of all individual reservoirs. The source regions of Incachaca, Hampaturi and Palcoma are connected to two WTPs; Chuquiaguillo and Pampahasi. See Table 5 for their demand and maximum capacity and future projections.

Table 5: Demand and capacity of the WTPs

WTP	2018				2022				2027	
	Demand		Capacity		Demand		Capacity		Demand	
	hm^3/year	l/s	hm^3/year	l/s	hm^3/year	l/s	hm^3/year	l/s	hm^3/year	l/s
Chuquiaguillo	6.47	208	9.46	300	6.97	224	9.46	300	7.62	245
Pampahasi	20.12	647	22.08	700	21.74	699	37.84	1200	25.01	804

2.1.3.1 Incachaca system

The Incachaca system is connected to two WTPs; Pampahasi and Chuquiaguillo. The connection with Pampahasi consists of a masonry channel with an approximate length of 12 km and capacity of 300 l/s. The associated loss of this channel is about 10%. The link with Chuquiaguillo is made from a 400 mm pipe with a transport capacity of 400 l/s and a loss of 1%.

There are four reservoirs within the Incachaca system, from upstream to downstream direction these are: Sorajahuira, Estrellani, Quinquillosa and Incachaca, see Table 6 for their basic characteristics. These four reservoirs are connected in a serial configuration, each discharging its water to the next by using the natural drainage network of the basin, see Figure 5.

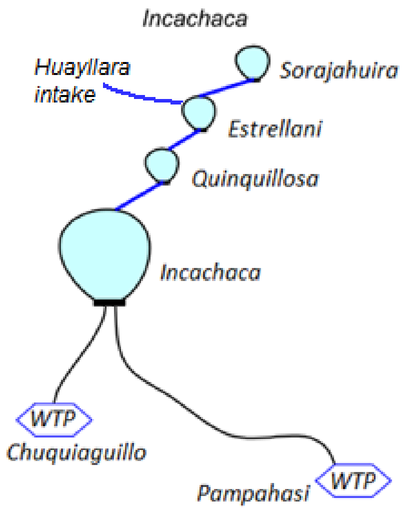

Figure 5: The Incachaca water supply system

Table 6: Basic characteristics of the reservoirs in the Incachaca system

Reservoir	Capacity	Surface area	Altitude
	hm^3	km^2	m
Incachaca	5.16	0.71	4369
Quinquillosa	0.37	0.08	4478
Estrellani	0.76	0.24	4638
Sorajahuira	0.26	-	-
Total	**6.55**	**-**	**-**

The Incachaca reservoir is the largest and most downstream, in 2015 its dam was raised to increase the storage capacity from 4.22 hm^3 to 5.16 hm^3. In comparison, the other reservoirs are quite small and serve the purpose of storing extra water within the basin and supplying it to the Incachaca reservoir. Sora Jahuira is the highest reservoir of the basin and its operation begins approximately in the month of August, when the level of the Incachaca reservoir begins to decline. The Sora Jahuira reservoir is generally emptied during one month of operation. The operation of the Estrellani and Quinquillosa reservoirs is also performed depending on the water level of the Incachaca reservoir.

In 2018 the Huayllara river intake was constructed in the Rio Pongo north of the Incachaca catchment. This intake allows to subtract water directly from the river for extra supply by pumping it over the mountains towards reservoir Estrellani. The extraction can take place from November until April with a maximum of 200 l/s, during the remainder of the year discharge in the Rio Pongo is too low for extraction.

2.1.3.2 Hampaturi system

The Hampaturi system is only connected with WTP Pampahasi. This connection consists of a 800 mm pipe with an approximate length of 13.5 km and a transport capacity of 1400 l/s. The associated loss of this pipeline is about 2.3%. Currently, the system consists of five reservoirs, from upstream to downstream direction: Kunkahuikara, Ajuan Khota, Serkhe Khota, Hampaturi Alto and Hampaturi Bajo, see Table 7 for their storage capacities. All reservoirs are connected by the natural drainage network of the basin, see Figure 6. The construction of Hampaturi Alto finished recently, and operation started in 2017.

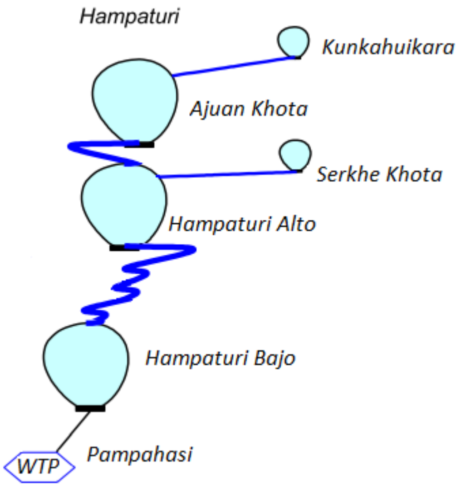

Figure 6: The Hampaturi water supply system

Table 7: Basic characteristics of the reservoirs in the Hampaturi system

Reservoir	Capacity	Surface area	Altitude
	hm^3	km^2	m
Hampaturi Bajo	3.02	0.41	4203
Hampaturi Alto	6.04	0.33	4321
Ajuan Khota	3.46	0.43	4429
Serkhe Khota	0.35	0.15	4799
Kunkahuikara	0.38	0.1	4566
Total	**13.25**	**1.42**	

The operation of the Ajuan Khota reservoir usually begins during the month of May when the water levels in Hampaturi Alto and Bajo reservoirs start to drop and ends in July. The dams at Kunkahuikara and Serkhe Khota serve the purpose of storing extra water within the basin during dry years. Consequently, their operation only occurs during these periods.

2.1.3.3 Palcoma system

The Palcoma catchment is only connected to WTP Pampahasi and does not possess any reservoirs. Water is directly taken from the river by a river intake, which was constructed in 2017. About 65% of the total river discharge cannot be extracted due to social and agricultural reasons. The potential extraction depends on the variable river discharge and the demand of downstream habitants and farmers. The Palcoma river is connected with WTP Pampahasi by a 600 mm pipe with a transport capacity of 500 l/s and an approximate loss of 2.3%.

When a precipitation event is recorded, the extraction at this river intake can be increased. This extraction is sometimes preferred over the supply from the Hampaturi system to save as much water as possible in the Hampaturi reservoirs. At river intakes the water usually has a high turbidity leading to high treatment costs. In years with normal or excessive runoff from the Incachaca and Hampaturi catchments, less or no water from the Palcoma intake will be necessary, reducing the treatment costs.

2.1.3.4 Pampahasi WTP

As described above the Pampahasi WTP has three supply sources: Incachaca, Hampaturi and Palcoma. Hampaturi is historically the most important supply source of the Pampahasi WTP. On average during the period of 2000 – 2011, 73% of the supply came from Hamapturi and 27% from Incachaca. The Pampahasi WTP supplies drinking water to the eastern and southern areas of La Paz and has a current production capacity of 700 l/s, which will be extended to 1200 l/s in 2022. The demand in 2018 was 20.1 hm^3/year (647 l/s). Currently, 85% of the 260,128 inhabitants within the Pampahasi distribution network are connected to the network. The physical and chemical quality of the water is good. In the rainy season turbidity peaks occur, caused by the drag material that reaches the WTP.

2.1.3.5 Chuquiaguillo WTP

The Chuquiaguillo WTP started production in 2018, has a capacity of 300 l/s and is supplied by the Incachaca system. The demand in 2018 was about 6.47 hm^3/year (208 l/s). After Chuquiaguillo WTP started working, the supply from the Incachaca system towards the Pampahasi WTP was strongly reduced. However, in dry situations when the Hampaturi reservoirs have insufficient water, it is possible to divert water from the Incachaca system through the existing channel towards the Pampahasi WTP. Operational control of this channel should be proactive before a shortage at the Pampahasi WTP occurs, due to the limited capacity of the masonry channel.

2.2 Data

An overview of all the data used in the methodology is presented in Table 8 and Table 9. Most data sets are provided by EPSAS, some additional data sets are obtained from various other sources. There is no metadata available for any of the data sets, except their location of measurement.

Table 8: Overview of the timeseries data sets used in the Methods section

Variable	Period	Resolution	Source
Incachaca (4369 m+MSL)			
Precipitation	2000 - 2016	Monthly	EPSAS
Spill	2000 - 2016	Monthly	EPSAS
Outflow	2000 - 2016	Monthly	EPSAS
Reservoir level	1999 - 2016	Daily	EPSAS
Hampaturi Bajo (4203 m+MSL)			
Precipitation	2000 - 2016	Monthly	EPSAS
Spill	2000 - 2016	Monthly	EPSAS
Outflow	2000 - 2016	Monthly	EPSAS
Reservoir level	1999 - 2016	Daily	EPSAS
Ajuan Khota (4429 m+MSL)			
Spill	2005 - 2016	Monthly	EPSAS
Outflow	2005 - 2016	Monthly	EPSAS
Reservoir level	1999 - 2016	Daily	EPSAS
Achachicala (4383 m+MSL)			
Precipitation	1991 - 2016	Monthly	EPSAS
Air temperature	1999 - 2016	Monthly	EPSAS
El Alto (4071 m+MSL)			
Precipitation	1943 - 2016	Monthly	EPSAS
Air temperature	1946 - 2016	Monthly	EPSAS
El Alto airport (4058 m+MSL)			
Air temperature	2013 - 2016	Hourly	METAR, El Alto
Humidity	2013 - 2016	Hourly	METAR, El Alto
Wind speed	2013 - 2016	Hourly	METAR, El Alto
La Paz (3592 m+MSL)			
Precipitation	1976 - 2005	Monthly	EPSAS
Sunshine	-	Monthly	World Weather & Climate Information
Daylight	-	Daily	U.S. Naval Observatory
Multi-Source Weighted-Ensemble Precipitation (MSWEP)			
Precipitation	1979 - 2014	Daily	EarthH2Observe

Table 9: Overview of other data used in the Methods section

Other data			
Object	Type	Resolution	Source
Digital elevation model (DEM)	Raster	30 meter	SRTM
Catchment and reservoir boundaries	Vector	-	RHDHV
Technical data catchments	Area	-	EPSAS
Technical data reservoirs	Area, Volume-water level relation, spill level, dead volume	-	EPSAS
Operational data WTPs	Demand, capacity	-	EPSAS

Monthly air temperature records are available for the Alto Achachicala station, located within the Choqueyapu basin (adjacent to Incachaca) and for a station located in El Alto. Additional air temperature records with an hourly interval are obtained from the weather service of the El Alto airport.

Precipitation is measured on a monthly resolution at the reservoirs Incachaca and Hampaturi Bajo with altitudes of 4369 and 4203 (m+MSL) respectively. Monthly measurements are also performed at the stations Alto Achachicala, El Alto and La Paz with altitudes of 4383, 4071 and 3592 (m+MSL) respectively. With only two measurement locations inside the study area, spatial distribution of precipitation is hard to estimate. The distribution of the rain gauges over the area is important, as is the distribution over different altitudes. Elevation can be crucial because clouds tend to be wind driven into valleys and might get trapped at certain elevations, resulting in the release of rain (Pillco et al., 2007).

Currently water levels are measured daily at the following reservoirs: Incachaca, Hampaturi Bajo and Ajuan Khota. The water levels are recorded manually by using a measuring tape. Using these water level measurements and waterlevel-volume relations, the stored reservoir volumes are estimated. The outflow is estimated by measuring the water levels at the WTP and translating those with a Q-h relationship. The same is done for the spill at the spillway. See Figure 7 for an overview of the monitoring locations.

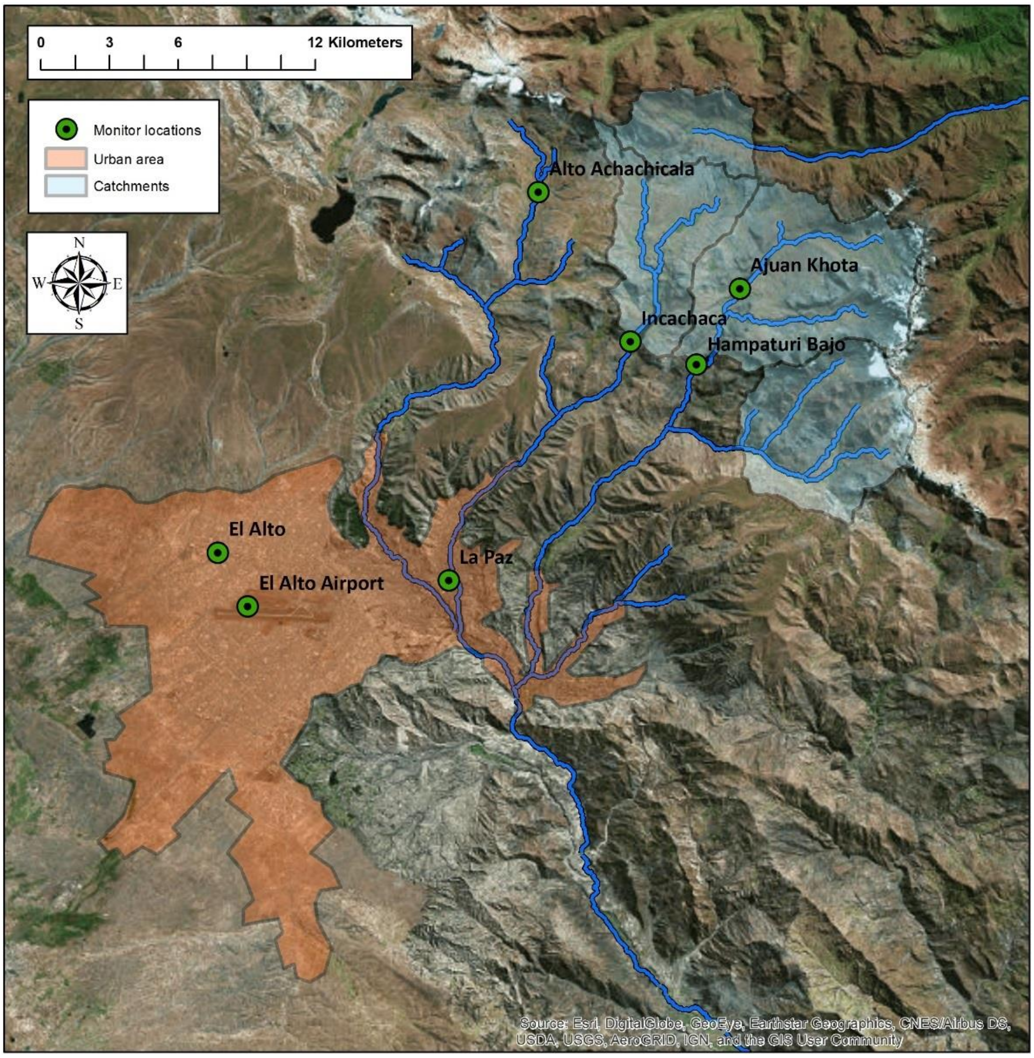

Figure 7: Overview of the monitoring locations

2.3 Tools

To achieve the research objective and answer the research questions, it is important to consider which tools are appropriate to use in this research and can be implemented in the methodology. First, the need of rainfall-runoff modelling is explained and then it is considered what a suitable type of model is. Secondly, the needs regarding the optimization framework is explained and then a suitable tool is chosen.

2.3.1 Rainfall-Runoff modelling

Rainfall-runoff models can be used for a variety of applications, e.g. simulation of streamflow records for design purposes, estimation of streamflow statistics in ungauged streams or assessment of human influence on hydrological processes (Bergström & Forsman, 1973). Within this thesis a rainfall-runoff model will be used to understand the hydrological behaviour of different catchments, e.g. the response time and differences in quick runoff and baseflow. Furthermore, it will be used to simulate stream flows for 'real-time' control purposes. Within this research, it is necessary to calculate discharges based on a combination of historical precipitation scenarios and varying initial hydrological conditions.

2.3.1.1 Model structures

According to Sitterson et al. (2017), roughly three model structures are available for rainfall-runoff models that calculate runoff very differently: empirical, conceptual and physical models. Empirical models, also called data-driven models, are the least complicated type and use (non)-linear regression between historical precipitation and discharge records (Devi et al., 2015). An example of an empirical model is the Curve Number method (Sitterson et al., 2017). Empirical models are often characterized as a black box, since very little is known about the internal processes that determine the hydrological behaviour (Sitterson et al., 2017). This type of model lacks realistic physical components and is therefore unsuitable for situations where other output besides runoff is needed (Devi et al., 2015). Furthermore, since empirical models do not include any components regarding storage, it is not possible to apply it in situations with varying initial hydrological conditions. Therefore, empirical models perform better when used on long time scales, when the impact of storage conditions on the model performance can be ignored (e.g. annual time steps) (Vaze, Jordan, Beecham, Frost, & Summerell, 2011). However, it is possible to simulate a more detailed catchment response by making a distinction between quick runoff and base flow by using two (non-) linear components (Jakeman & Hornberger, 1993).

Conceptual models introduce physical components to represent simplified hydrological processes. These models are based on a water balance including evapotranspiration and groundwater to provide the user with a conceptual idea of the behavior of the catchment (Sitterson et al., 2017). They consist of one or multiple reservoir storages and simple mathematical equations to distribute the precipitation among the different storages and outputs (Devi et al., 2015). The introduction of water storage makes it possible to include varying initial hydrological conditions. Conceptual models vary in complexity, depending on the number of model components and the sophistication of the model equations. These models need to be calibrated using a large number of historical precipitation, evapotranspiration and discharge records (Devi et al., 2015). Some conceptual models can include components such as snow and glaciers, however this will lead to an increase in data demand, computational times and additional calibration parameters (Vaze et al., 2011).

Physical models are the most complicated type of rainfall runoff models, representing the physics related to the hydrological processes (Sitterson et al., 2017). Physical laws used include conservation of mass and energy, momentum and kinematics. The internal structure of these models is similar to real-world systems. The advantage of physical models is the clear connection between model parameters and physical characteristics of the catchment (Devi et al., 2015). These models have extensive data requirements and can only be used when the physical properties underlying the hydrological processes are accurately understood (Sitterson et al., 2017). Usually physical models are only applied on small spatial scales due to the data requirements and computational times.

2.3.1.2 Spatial structures

Another classification of rainfall-runoff models can be made based on their spatial structure, making a distinction between lumped, semi-distributed and fully-distributed models. Lumped models consider a catchment as one unit, neglecting any spatial variability of precipitation, potential evapotranspiration and model parameters within the catchment (Vaze et al., 2011). Semi-distributed models can include relevant spatial characteristics, e.g. varying climatic and soil conditions or differences in land cover by dividing the catchment in sub-catchments (Sitterson et al., 2017). This effectively leads to a series of lumped rainfall-runoff models. Fully-distributed models process spatial variability by introducing grid cells, with each individual cell having its own characteristics. Including spatial variability in a hydrological model will lead to an increase in data demand and computational time (Vaze et al., 2011).

Empirical models are usually lumped, predicting the runoff for an entire catchment, disregarding spatial information. Conceptual models can be set up in a lumped way, but it is also possible to include varying spatial characteristics of the catchment to build a semi-distributed or grid-based model. Physical models are always set up using a grid.

2.3.1.3 Model choice

According to Devi et al. (2015) the best model is one which gives the best results by using the least model parameters and is the least complex. From that perspective, a conceptual rainfall-runoff model is preferred within this thesis, since it offers multiple advantages over the other model types.

Conceptual models offer insight into the hydrological processes and behavior of the system, while still having a simple model structure, modest data input requirements and computational times. Since this thesis also focuses on understanding the hydrological behavior, it is important to study the hydrological processes. Also, conceptual models include water storage in the model structure making it possible to include the impact of varying initial hydrological conditions on the runoff. This is an important feature, since the state of the groundwater storage can have a substantial impact on the short-term runoff. Furthermore, conceptual models offer flexibility, it is possible to include spatial variability and different model components depending on the application and data availability. Physical models are not suitable for this thesis, since their data demands and computational times are too extensive.

It is chosen to model the rainfall-runoff process using the HBV model. HBV is a conceptual model and is applied frequently in a lot of countries under varying conditions, therefore a lot of case studies and literature about the model are available (Wetterhall, 2014). Furthermore, Wetterhall (2014) argues that HBV offers a good balance between complexity, performance and data requirements and it also avoids over parameterization. These are important requirements, since the available data within the study area is limited. By implementing the HBV-model in Python, it becomes very flexible and can be adjusted according to the user’s needs, e.g. adjusting the length of the time steps and iteratively adding model components and spatial information.

2.3.1.4 HBV-model structure

A model setup will be used according to the HBV-96 model as described by Lindström et al. (1997). See Figure 8 for its corresponding model structure.

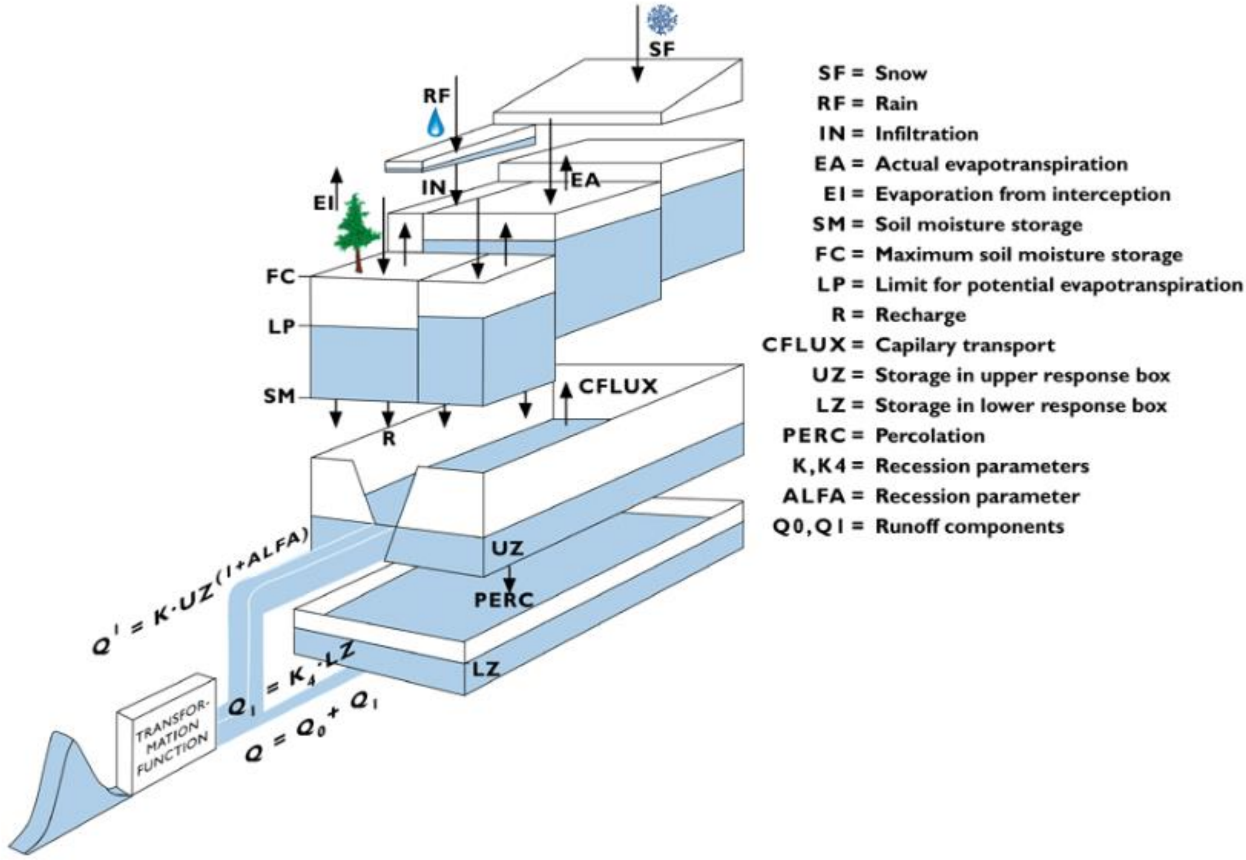

Figure 8: The model structure of HBV-96 (Lindström et al., 1997)

The HBV-96 model structure can be split in two parts; the basic model setup and the snowmelt-routine. The basic model setup is presented in Figure 9.

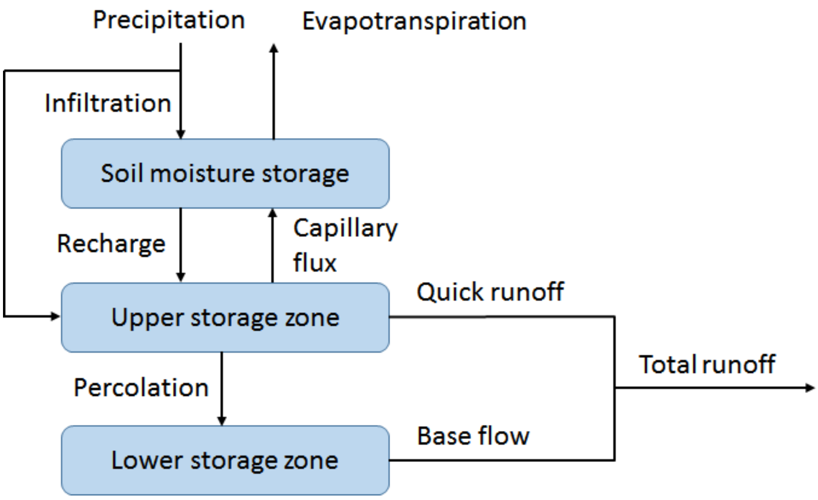

Figure 9: Schematization of the basic HBV-model structure as used within this study

The only water input is precipitation, which will infiltrate (INF) [mm] into the soil moisture storage until it is saturated. Any excess precipitation will directly flow into the upper storage zone as direct runoff (DR)

[mm]. The water that is stored inside the soil moisture storage will partly evaporate according to the amount of stored water and the potential evapotranspiration (PET) [mm]. The evapotranspiration (ET) [mm] is calculated according to Eq. (1):

$$ET = \begin{cases} PET \cdot \dfrac{SM}{LP \cdot FC} & \text{if SM} < \text{FC} \\ PET & \text{if SM} \geq \text{FC} \end{cases} \tag{1}$$

where: SM is the water stored in the soil moisture storage [mm]
LP is the limit for evapotranspiration [mm]
FC is the maximum capacity of the soil moisture storage [mm]

Water from the soil moisture zone will recharge (R) [mm] the upper storage zone and the capillary flux (CF) [mm day^{-1}] flows in the inverse direction. Water will also flow out of the upper storage zone as percolation (PC) [mm day^{-1}] into the lower storage zone and quick runoff (Q_{uz}) [mm day^{-1}] leaving the basin. These fluxes are calculated as follows:

$$R = INF \left(\frac{SM}{FC}\right)^{\beta} \tag{2}$$

$$CF = CFlux \frac{FC - SM}{FC} \tag{3}$$

$$Q_{uz} = K_f \cdot h_{uz}^{(1+\alpha)} \tag{4}$$

$$PC = PERC \cdot \left(\frac{SM}{FC}\right)^{\beta} \tag{5}$$

where: β is a soil parameter [-]
$CFlux$ is the maximum capillary flux [mm day^{-1}]
k_f is a recession coefficient [day^{-1}]
h_{uz} is the water stored inside the upper storage zone [mm]
α is a recession coefficient [-]
$PERC$ is the maximum percolation flux [mm day^{-1}]

The base flow (Q_{lz}) [mm day^{-1}] is calculated according to Eq. (6):

$$Q_{lz} = K4 \cdot h_{lz} \tag{6}$$

where: $K4$ is a recession coefficient [day^{-1}]
h_{lz} is the water stored inside the lower storage zone [mm]

In addition to the basic HBV model setup, a snowmelt routine can be added. The standard snowmelt routine as used in the HBV-96 model is based on a degree-day-approach (Lindström et al., 1997), which assumes an empirical relationship between snow melt and air temperature (Hock, 2005). It is decided not to include the snowmelt-routine in the rainfall-runoff modelling of this study, since the uncertainty of the available temperature data will greatly impact the results of the snowmelt-routine. Furthermore, the local relation between elevation and temperature is unclear. It is also questionable how large the contribution of snowfall and snowmelt is to the runoff, since the freezing conditions coincide with the dry season.

2.3.2 Optimization tool

To make decisions regarding an appropriate tool for defining and consecutively solving the optimization problem, some context is needed. First, some common optimization approaches in handling different goals will be described. Then, the model components needed to establish an optimization problem are presented. Subsequently, some conditions which are important for solving optimization problems are explained and finally, an appropriate tool is chosen and described.

2.3.2.1 Optimization approach

Optimization problems can often be classified in multi-objective optimization or single-objective optimization. In environmental systems conflicting goals are common, where there is often too much or too little water to fully satisfy all goals, resulting in multi-objective optimization problems.

According to Savic (2002), the main purpose of single-objective optimization is to find a global solution, which corresponds to the minimum or maximum of a single objective function. Marler & Arora (2004) argue that multi-objective optimization can be described as the process of optimizing systematically and simultaneously a collection of objective functions. They argue as well that in contrast to single-objective optimization, there is no single most optimal solution of a multi-objective problem. The interaction among conflicting objectives leads to a set of compromised solutions resulting in a trade-off, also known as a Pareto-front (Savic, 2002). According to Baayen et al. (2016), a solution on the Pareto-front is called Pareto optimal and it can be defined as the space of solutions satisfying the constraints for which no goal can be improved without negatively impacting other goals.

The following approaches are common in solving multi-objective optimization problems; converting the multi-objective problem into a single-objective problem, the weighting method and the sequential goal programming method (Rani & Madalena, 2010) (Savic, 2002) (Marler & Arora, 2004).

Rani & Madalena (2010) argue that a multi-objective problem can be reduced into a single-objective one by treating all objectives except for one as constraints. They explain that this approach is considered most suitable for generating different trade-offs among conflicting objectives. According to Savic (2002) there is an alternative method to convert a multi-objective problem into a single-objective one. By expressing all objectives using identical units, it is possible to allow an equal comparison among different uses. An example is the hydro-economic approach, which includes the operational costs and economic benefits of a water system by monetizing all objectives (Harou et al., 2009). Damage from unsatisfied objectives can be included by introducing penalty functions (Lund & Ferreira, 1996).

The weighting method handles the optimization problem by assigning weights to each objective and simultaneously solving all the individual objective functions (Labadie & Asce, 2004). This approach is usually preferred when many objectives are involved (Rani & Madalena, 2010). A drawback of the weighting method is that it introduces a degree of arbitrariness to the optimization problem (Baayen et al., 2016). With sequential goal programming individual objectives are ordered beforehand and are consequently solved in the provided order (Marler & Arora, 2004). Miltenburg (2018) argues that sequential goal programming is particularly suited for systems with clear priorities regarding the different objectives and where the trade-off between these objectives is modest. Furthermore, sequential goal programming offers more understanding of the optimization problem in contrast to using the weighting method.

2.3.2.2 Model components

The following model components are needed to establish an optimization problem:

1) A representation of the physical system
2) Initial conditions acting as the current state of the system
3) Boundary conditions, e.g.; inflows, outflows
4) Decision variables to control the system
5) Goal(s) to evaluate the system performance

Together these components define an optimization problem, which should be discretized in time and solved by a mathematical optimization algorithm. This should result in control actions that meet the specified goal(s) as well as possible for the given time horizon using the solution space provided by the boundary conditions.

2.3.2.3 Solver conditions

To model a water supply system and optimize its operational control, an optimization algorithm is needed that can solve the optimization problem. According to Baayen et al. (2016), in general it is desirable that the conditions below can be fulfilled when solving optimization problems.

1) Feasibility: there is a feasible solution
2) Stability: the solution is stable
3) Determinism: different initial solutions lead to identical optimal solutions

Feasibility means that it is possible to arrive at a solution without violating any boundary conditions (Marler & Arora, 2004). Stability refers to the situation where small changes to the solution space do not result in extensive changes of the solution. Determinism means that with varying starting solutions the optimization algorithm arrives at identical optimal solutions (Baayen et al., 2016). Together these conditions can help to decide what optimization method and tool are suitable for a specific optimization problem.

The operational control of the water supply system in this case study is characterized by two objectives; minimize the water shortages at the WTPs and minimize the operational costs. This can be classified as a multi-objective problem, since potentially conflicting objectives need to be optimized simultaneously. Reducing the amount of water shortages, means using the intakes more frequently, which results in higher costs. Lowering the costs will unconditionally result in more water shortages. However, by reformulating the first goal into the following; satisfy the demand of the WTPs, it becomes a boundary condition. In this way a clear hierarchy is added to the optimization problem, since satisfying the demand of the WTPs now always has priority over minimizing the operational costs. This clear hierarchy expands the solution space, making it easier to meet the feasibility condition.

The stability and determinism conditions are satisfied when the optimization problem becomes convex, which always leads to the existence of a global optimal solution. With non-convex problems, a local optimum might be found which is not necessarily the global optimum, leading to non-optimal solutions. Non-convex problems might encounter stability issues as well, where slightly different numerical settings can lead to very different results. Another downside of non-convexity is that minor changes in the initial conditions or boundary conditions may lead to other local minima, which can be totally different solutions.

The convexity of this optimization problem is guaranteed, since all relations are already linear. The relationship between the intake discharge of the river intakes and the associated costs is linear, because the costs of taking in an m^3 of water is constant. Therefore, the goal regarding the cost minimization can just be expressed in m^3 of water. Also, the amount of water stored inside the reservoirs can be expressed in m^3 of water, avoiding the use of a volume/water level relationship, which would lead to non-convexity.

2.3.2.4 Choice of optimization tool

It is decided to use RTC-Tools for solving the optimization problem within this case study. RTC-Tools offers two approaches to facilitate the optimization of objectives; sequential goal programming and the weighting method. The clear hierarchy of the optimization problem in this case study matches with the sequential goal programming method. Within the sequential goal programming method of RTC-Tools the optimal solution of an individual goal is added as a constraint to the optimization problem of all consecutive goals (Baayen et al., 2016). In other words, the optimization of all following goals is not allowed to worsen the solution of the previous goal.

RTC-Tools possesses some other properties which makes it suitable for this optimization problem. It is possible to make a distinction between soft and hard goals or constraints. In contrast to hard constraints, soft constraints are allowed to be violated if the solution space otherwise is not able to provide any feasible solutions. In this way the feasibility condition can be guaranteed.

Setting up an optimization problem in RTC-Tools can be done without having expert knowledge on numerical discretizations and mathematical solving algorithms. In RTC-Tools the model that represents the physical water system is build using predefined model components. This makes it convenient for the user to model the physical water system. Another advantage of RTC-Tools is the flexibility it offers to the user. The optimization problem is defined in Python, including the initial conditions, boundary conditions, decision variables and goals, which makes it very customizable. Each of these components can be adjusted easily to evaluate its impact on the optimized solution. Furthermore, it is possible to use RTC-Tools as a subpart of a larger model or script programmed by the user, e.g. in a loop to solve the optimization problem for different combinations of initial conditions and boundary conditions. This makes a wide variety of applications possible.

2.3.2.5 RTC-Tools

The RTC-Tools software is an open-source toolbox from Deltares and it is specifically designed for control and multi-objective convex optimization of environmental systems under forecast uncertainty (Baayen et al., 2016). In RTC-Tools the model that represents the physical water system is build using the open-source software Modelica, which is an object-oriented programming language. Deltares provides two libraries in Modelica containing various components that can be used to build a network of rivers, channels, reservoirs and hydraulic structures. The user can choose between the channel-flow library and the simple-routing library. The first includes different components and links which can be used to describe hydraulic processes. The latter restricts to describing the water balance.

Within RTC-Tools the model of the water system is typically set up once and then used every time again for different initial conditions, boundary conditions and goals. The goals and constraints are applied to individual components or in- and outputs of components from the Modelica model. For this case study, it is chosen to represent the water system by simple-routing components. Any hydraulic behavior of the water system e.g. routing or backwater effects are not relevant, since the time scale of the hydraulic processes is much shorter than the timescale considered in this water allocation analysis. Important hydraulic characteristics of the system such as the flow capacity of pipelines and the storage capacity of reservoirs are included as constraints during the optimization process.

There are four simple-routing components available; Inflow boundaries, terminal boundaries, nodes and reservoirs. The inflow and terminal boundaries specify any upstream and downstream boundary conditions respectively. Water enters the system at the inflow boundaries and exits the system at the terminal boundaries. Nodes are used for modelling confluences, bifurcations or combinations thereof and reservoirs can store water. These model components have so-called connectors, which specify the input and the output of each component to make connections with other components. All types of components can only have a single input and output, except for the nodes. Nodes may have multiple inputs where the flows are summed and distributed among one or multiple outputs. Note that all model equations are implemented in Modelica in a continuous form. The time discretization is carried out at a later stage by RTC-Tools.

3 Methods

This chapter of the report presents all the methods which are used to produce the results and answer the research questions. The methods chapter is split into two parts according to the main research questions; the rainfall-runoff modelling and the optimization process.

3.1 Rainfall - runoff modelling

To understand the functioning of the natural water system and determine the hydrological boundary conditions for the water supply system, a rainfall-runoff model is set up. As explained in section 2.3.1.3 the rainfall-runoff process is modelled using the HBV-model. This section is divided in the following order; data requirements, the HBV-model setup, a sensitivity analysis and finally the calibration and validation.

3.1.1 Data requirements

To setup the HBV-model and simulate runoff, two types of input data are required; precipitation and PET. Subsequently, to execute the calibration and validation process also discharge data is needed of the modelled catchments. As shown in the overview of the used data in chapter 2.2, the precipitation is available over the period 2000 – 2016 and only measured at the most downstream locations within the catchments. Whereas, temperature measurements are only available for stations located outside the study area. It is important to perform an elevation correction on data that is collected at a different altitude than the altitude where it is applied. In this way the data becomes representative for their entire catchment areas. See appendix A1 for the calculation and application of the elevation correction.

There is no PET data available for the study area, so PET values are calculated. Because of limited data availability it is not possible to calculate the PET for the entire 2000 – 2016 period. Therefore, it is decided to calculate the daily PET for an average year, based on data from the period 2013 – 2016, see appendix A2.

The discharge data is calculated based on the reservoir balance of the major reservoirs. As shown in the data overview in chapter 2.2, the outflow, spill and reservoir levels are available for the Incachaca, Hampaturi Bajo and Ajuan Khota reservoir. See appendix A3 for the calculation of the discharge data.

3.1.2 HBV-model setup

It is decided to model Hampaturi as an entire catchment and also model Hampaturi Bajo and Ajuan Khota as separate catchments. In that way, it can be decided which partition method results in the best model performance, see appendix A6 for the separate models of Hampaturi Bajo and Ajuan Khota. This decision is also affected by the schematization of the reservoir system in the optimization section of this research.

The HBV model structure as presented in section 2.3.1.4 including the model fluxes and storage zones is implemented in a Python script to calculate their corresponding values on a daily time interval. The model fluxes should be implemented in a very distinctive order to prevent the occurrence of negative storages and fluxes. First, the vertical downward fluxes are calculated and added/subtracted to/from their respective storages. Afterwards the storages are updated and then the vertical upward fluxes are calculated and applied to their respective storages. Again, the storages are updated and finally the horizontal fluxes are calculated and applied.

The available precipitation data has a monthly resolution, which is transformed to a daily resolution by dividing the monthly precipitation by the corresponding number of days. The discharge dataset also has a monthly resolution but cannot be disaggregated, therefore the calibration and validation are performed on a monthly basis. The basic model setup as shown in Figure 9 is implemented and calibrated and validated.

3.1.3 Sensitivity analysis

A sensitivity analysis of the basic HBV-model is performed to get an indication of the impact of the individual model parameters on the model performance. This is also beneficial during calibration, since this will provide a focus on which parameters are important to calibrate. The sensitivity analysis is performed on the Hampaturi basin using a precipitation lapse rate of 0.02 % and the initial model parameters according to Table 10.

Table 10: Initial settings of the model parameters, including the resulting RVE and NS

LP [mm]	FC [mm]	Alpha [-]	Kf [day-^{1}]	Beta [-]	CFlux [mm day^{-1}]	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS [-]
0.75	300	1	0.2	3	0.1	1	0.05	-6.33	0.659

The model parameters were consecutively varied between -50% and +50%, while the other parameters were kept constant. In order to quantify the performance of the model, two indicators are used; the Nash-Sutcliffe coefficient (NS) and the Relative Volume Error (RVE). To calculate these indicators on a monthly basis, the simulated daily discharges are aggregated to monthly values. Since the hydrological model serves two goals; predicting the low flows during the dry season and the peak discharges during the wet season, it was chosen to use NS to assess the model performance during the wet season (Nov – Apr) and RVE during the dry season (May – Oct). Because the wet season does not exactly occur at the same time each year, it is chosen to use NS over the period Nov – Apr instead of Dec – Mar. These indicators can be calculated according to Eq. (7) and Eq. (8):

$$NS = 1 - \frac{\sum_{t=1}^{T}(Q_{sim}^{t} - Q_{obs}^{t})^2}{\sum_{t=1}^{T}(Q_{obs}^{t} - \overline{Q_{obs}})^2} \tag{7}$$

$$RVE = \frac{\sum_{t=1}^{T}(Q_{sim}^{t} - Q_{obs}^{t})}{\sum_{t=1}^{T}(Q_{obs}^{t})} \tag{8}$$

where: Q_{sim} is the simulated discharge at time t
Q_{obs} is the observed discharge at time t

3.1.4 Calibration and validation

The calibration and validation are performed according to a split sample test. The precipitation and discharge datasets are split in two parts with (approximately) equal length. For Incachaca the period 2000 – 2008 is used for calibration and 2009 – 2016 for validation. For Hampaturi the period 2005 – 2010 is used for calibration and 2011 – 2016 for validation. The goal of the validation is to give a realistic indication of the model performance, when it is used with 'new' input data. Alternatively, the models are also calibrated based on the entire dataset; 2000 – 2016 and 2005 – 2016 for Incachaca and Hampaturi respectively. The calibration using the entire dataset is also applied to the HBV-models for Hampaturi Bajo and Ajuan Khota, see appendix A6.

According to the results of the sensitivity analysis, it is decided to calibrate the models using the parameters LP, FC, beta, Perc and K4, see section 4.1.2. for the results of the sensitivity analysis. The parameters alpha, kf and CFlux will remain with the settings as presented in Table 10.

It is decided to evaluate the model performance during the dry season using RVE, because during this season the total volume of discharge is considered more important than the variability of it.

Underestimations of discharge during the dry period could implicate shortages which would not be present in reality. Whereas, overestimations could implicate situations with a sufficient water supply, while in reality a shortage would occur. The model performance during the wet season is evaluated using NS, since the shape and timing of the discharge peaks are considered more important than the total volume. The shape and timing of the peak can have a major impact on the spill behavior of the reservoirs. During the calibration, an RVE smaller than 5% is regarded sufficient, while NS should be closest to 1 as possible. The ranges which are used to vary the calibration parameters are shown in Table 11.

Table 11: Calibration ranges of model parameters

Model parameter	**Parameter range**
LP [-]	[0.4 – 1.0]
FC [mm]	[40 – 200]
Beta [-]	[1 – 6]
Perc [mm day^{-1}]	[1 – 30]
K4 [day-^{1}]	[0.01 – 0.3]

There is one outlier in the data that is notable, which is the precipitation of Hampaturi during the wet period of 2007-2008. This period shows a major difference between the precipitation and discharge in comparison to the other wet periods. The calibration and validation for Hampaturi are performed including and excluding this specific wet period to see its effect on the model performance.

3.2 Optimization and long-term simulation

This section of the methods focuses on the optimization of the water supply system and the long-term simulation. First, the optimization using RTC-Tools is explained. Then, the long-term simulation and decision support on real-time control is described.

3.2.1 Optimization using RTC-Tools

To translate the supply system into an optimization problem and implement it in RTC-Tools, the system and its different control options are described. Then the optimization problem is defined and consequently its implementation in RTC-Tools is described.

3.2.1.1 System description and control options

The water supply system consists of multiple infrastructural components; reservoirs, river intakes, WTPs and pipelines, see Figure 10. The reservoirs are supplied by runoff from rainfall inside the Incachaca and Hampaturi catchments. Due to the limited data availability it is not possible to establish separate HBV models for the individual reservoirs within the catchments. It is decided to implement the different reservoirs in RTC-Tools as one virtual reservoir per catchment. Hampaturi could be split in two catchments, according to the Ajuan Khota and Hampaturi Bajo reservoirs. However, as explained in appendix A6, the performance of these separate models is worse in comparison to the model representing the entire Hampaturi catchment.

The Palcoma catchment does not possess any reservoirs, but it is possible to use its runoff by taking water from the Palcoma River via the intake directly to WTP Pampahasi. Furthermore, it is also possible to supply WTP Pampahasi with the Incachaca and Hampaturi catchments. WTP Chuquiaguillo can only be supplied by Incachaca. Huayllara is the second intake, which can pump water from an external catchment towards Incachaca. The use of the intakes carries added costs, represented by costs for pumping and extra costs associated with cleaning the sediment-rich water of the Palcoma River.

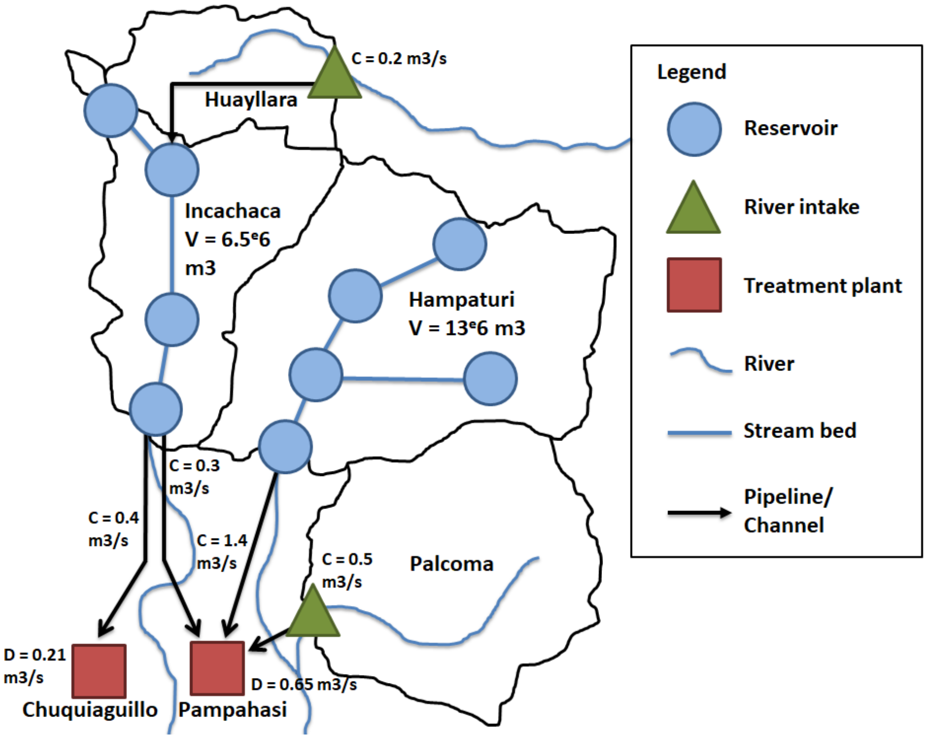

Figure 10: Schematization of the water supply system; V is volume, C is capacity and D is demand

From an operational point of view there are only five control options, since the control options on the individual reservoirs are disregarded. These control options are represented in Figure 10 by the different pipelines. The operator can decide for every pipeline what the flow will be by using valves. In this way, the operator is able to use the water supply system in an effective manner. For example, the channel between Incachaca and Pampahasi can be used to supply WTP Pampahasi when water shortages occur at Hampaturi or when Incachaca has an excess of water. Transporting water using the pipelines also leads to water losses, see Table 12 for the associated losses.

Table 12: The pipelines and their associated losses

Pipeline	Loss
Incachaca - Chuquiaguillo	1 %
Incachaca - Pampahasi	10 %
Hampaturi - Pampahasi	2.3 %
Palcoma - Pampahasi	2.3 %

Since this water supply system is still an environmental system, it is also associated with future uncertainty in natural conditions. The water supply system is constraint by the future flows into the reservoirs and the Palcoma and Huayllara rivers. Usually the river intakes have the greatest water availability during the wet-season (nov – apr), since stream flows are high during that period. In the dry-season (may – oct) it is often not possible to subtract water. The optimized operational control of the intakes will be proactive by taking water already during the wet season to store sufficiently in the reservoirs for use during the dry season. There is also an outflow constraint at the Palcoma River. EPSAS determined that at least 65% of the flow in the Palcoma River should be conserved due to the social dependence of downstream residents and farmers, so only 35% is available for the intake. Furthermore, it is assumed that during the dry season no intake is possible at Palcoma and Huayllara.

3.2.1.2 Definition of optimization problem

The operator aims to prevent water shortages at the WTPs and minimize the extra costs associated with the use of the intakes. In other words, the operational control of the water supply system needs to be optimized according to two objectives; minimizing the water shortages and minimizing the added operational costs. As described in section 2.3.2.4 this multi-objective problem can be reduced into a single-objective problem by setting the demand of the WTPs as a constraint.

The solution space of the cost minimization function is now constrained by the following boundary conditions; the inflows at Incachaca, Huayllara, Hampaturi and Palcoma, the social constraint at the Palcoma River and the demand constraints of the WTPs. The inflows at Incachaca, Hampaturi and Palcoma are calculated by their respective HBV-models. According to EPSAS, at the Huayllara intake 0.2 m^3/s is available during the wet season (nov – apr), so this is implemented as boundary condition in the optimization problem.

As mentioned above, from an operational point of view there are five control options to operate the water supply system. However, from an optimization perspective, there are only three degrees of freedom available to minimize the extra costs. Since the demands of the WTPs are added to the optimization problem as fixed constraints, the supply to WTP Chuquiaguillo is not a degree of freedom (there is no alternative supply source). Also, the supply from Hampaturi to WTP Pampahasi is not a degree of freedom, since this supply automatically follows from the control actions on the Palcoma intake and the Incachaca-Pampahasi channel. So, the following control options are degrees of freedom; the intakes at Huayllara and Palcoma and the Incachaca-Pampahasi channel.

3.2.1.3 Implementation in RTC-Tools

The model of the physical system as schematized in Modelica is shown in Figure 11. Only simple-routing components are used to build this model, since merely the water balance is of importance in this study. See section 2.3.2.5 for an explanation about the different RTC-Tools model components. The inflow locations of Incachaca, Huayllara, Hampaturi and Palcoma are represented by inflow boundaries. Nodes are used to model confluences and bifurcations, since this is the only component that might have multiple inputs where flows are summed and distributed among one or multiple outputs. Therefore, nodes are used to represent the intakes of Huayllara and Palcoma. The inflow boundaries are connected to these nodes having two outputs; the regulated intake flow and the outflow. The regulated intake flow from Huayllara is connected to the virtual reservoir of Incachaca, while the regulated intake flow from Palcoma is connected straight to WTP Pampahasi.

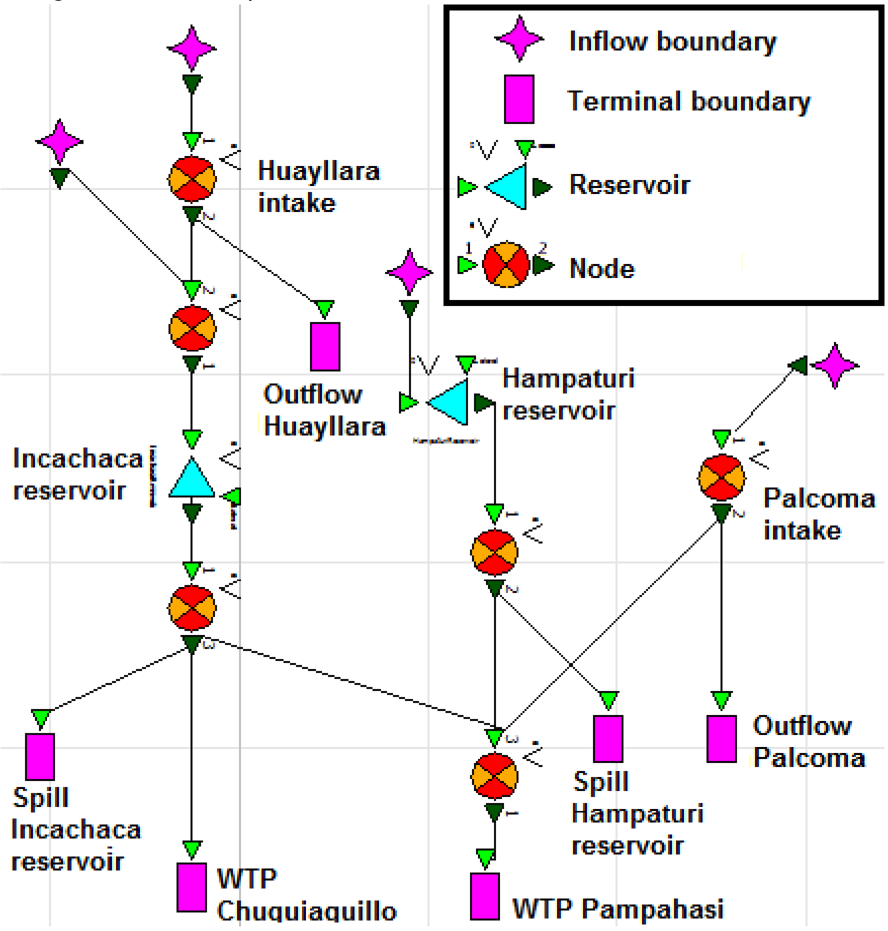

Figure 11: Schematization of the physical model of the water supply system in Modelica

As explained in section 3.2.1.1, it is decided to implement the different reservoirs in RTC-Tools as one virtual reservoir per catchment. This is achieved by adding the storage volumes of the individual reservoirs. The modelling of reservoir spill also involves nodes by connecting the reservoirs to nodes having two or three outputs; the directed flow and the spill. The directed flow from reservoir Incachaca is connected to two WTPs, while the directed flow from reservoir Hampaturi is connected to a single WTP. The WTPs and spill locations are represented by terminal boundaries. The social constraint at the Palcoma River is implemented in the preprocessing of the data. After HBV calculated the river flows, it is multiplied by 0.35 to represent the flow available for the intake.

The pipeline losses cannot be implemented into the physical model and are therefore introduced by raising the demands of the WTPs. The demand of WTP Chuquiaguillo is increased with 1% according to the loss of the Incachaca – Chuquiaguillo pipeline. The demand of WTP Pampahsi is increased by 2.3% according to the losses of the Hampaturi – Pampahasi and Palcoma – Pampahasi pipelines. Unfortunately, this approach makes it impossible to implement the loss of the Incachaca – Pampahasi channel, which is 10%. The 2.3% loss of the pipelines connected to Pampahsi also applies to the Incachaca – Pampahasi channel, leading to an incorrect loss in this channel.

Python is used for the definition of the goals and constraints and how the water supply system should be optimized. These goals and constraints can be applied to individual components, or to specific in- or outputs of components, within the Modelica model. In RTC-Tools sequential goal programming is used to perform the optimization of different goals in a specific order. The priority list for this water supply system looks as follows:

1. Satisfy the demand constraint for the Chuquiaguillo WTP;
2. Satisfy the demand constraint for the Pampahasi WTP;
3. Minimize the flow at the Huayllara intake;
4. Minimize the flow at the Palcoma intake;

First the demand of the Chuquiaguillo WTP is satisfied and consequently the demand of the Pampahasi WTP. This should prevent the solver from directing water from Incachaca towards Pampahasi in case the demand at Chuquiaguillo is not yet satisfied.

When the WTP demands are met, it is possible to minimize the use of the intakes. By minimizing the flow at the intakes, the minimization of the extra costs can be guaranteed. According to EPSAS the additional costs for pumping at Huayllara is 0.18 €/m3 and the additional costs for cleaning the sediment-heavy water of the Palcoma River is 0.19 €/m3. If the Huayllara intake is to be used to supply Pampahasi, the water needs to flow via the Incachaca – Pampahasi channel, which has an estimated loss of 10%. Therefore, the Palcoma intake is still a more viable option than the Huayllara intake and minimization of the Huayllara intake has priority over the minimization of the Palcoma intake. Furthermore, this decreases the impact of the incorrect implementation of the loss in the Incachaca – Pampahasi channel on the optimized control actions.

The time discretization takes place in months and because the different months do not have an equal length, it is chosen to use the forward Euler discretization scheme. The forward Euler scheme uses the Qin and Qout of the first timestep, whereas the backward Euler scheme uses the Qin and Qout of the second time step. For calculating the reservoir balance RTC-Tools uses the length of the first-time step. The use of backward Euler would result in a mismatching length of the different time steps. In order to optimize multiple scenarios, the ensemble mode is turned on. When the Python script containing the problem definition is finished, it can be run to start RTC-Tools.

3.2.2 Long-term simulation and decision support on real-time control

This section of the methods focuses on the long-term simulation and the decision support on real-time control. First it is explained what the basic concepts of this long-term simulation are and how it is executed. Then the implementation of the 'real-time' control is described.

3.2.2.1 Model predictive control

By introducing the uncertainty of future precipitation to the single-objective optimization problem, in essence the problem becomes multi-objective again. During the real-time control process, the operator must make a compromise based on the interaction among the conflicting objectives of minimizing the water shortages and minimizing the operational costs. This is also known as a trade-off. An optimization problem that is susceptible to forecast uncertainty calls for a technique that explicitly takes this uncertainty into account (Baayen et al., 2016).

To make a long-term simulation of the 'real-time' control process and implement the decision support, a model predictive control (MPC) is established. According to Schwanenberg et al. (2015) MPC is based on a combination of forecasting and optimization. They state that the following are key elements of MPC: (1) prediction of future trajectories of the uncontrolled variables on a finite time horizon, (2) calculation of control actions that optimize an objective function and (3) after the application of the selected control actions the forecast horizon shifts ahead in time.

Scenarios based on historical precipitation data are used as prediction for possible future trajectories of precipitation. For every scenario the most optimal control actions are determined by RTC-Tools. This gives the operator the opportunity to choose control actions based on a variety of possible futures. Then, the operator chooses which control actions will be implemented by considering the likelihood, being precautionary or based on expert judgement. Within this simulation the decisions regarding the 'real-time' control actions are executed based on control strategies.

3.2.2.2 Definition of scenarios

According to Bargiela (1993), operational control needs to consider what effect any decision has on the future and how far into the future this effect applies. Furthermore, it is important to consider the final state of the system, since the water system will continue to operate after the control horizon is expired. To determine the control actions during the wet season, the next wet season should already be considered. This interannual variability of precipitation and runoff is captured by introducing a time horizon of at least one year. To establish a proper final condition of the system and prevent the reservoirs from being empty at the end of the time horizon, scenarios with a length of two years are introduced. It is chosen to use the historical precipitation (2000 – 2016) dataset as 17 individual scenarios, where each scenario is a repetition of two consecutive hydrological years, defined as the period from July to June.

3.2.2.3 Definition of control strategies

The compromise between the conflicting objectives will never lead to the most optimal solution of the multi-objective problem. A conservative approach leads to a considerable use of the intakes, which at a later moment in time might prove to be unnecessary. When it turns out that there is plenty of precipitation it becomes apparent that the use of the intakes could have been lower. But, when the future proves to be dry, this strategy can prevent a major water shortage. In other words, a conservative control strategy is expensive, while a riskier control strategy is cheaper.

The control strategies are defined in such a manner that the control actions are chosen in a consistent way throughout the entire simulation. After RTC-Tools optimized the control actions for every individual scenario, the set of control actions on the intakes of Huayllara and Palcoma is sorted from large to small based on their intake discharge. The most conservative strategy always choses the first control actions, corresponding to the largest intakes. This does not necessarily lead to control actions for Huayllara and Palcoma belonging to the same optimized scenario. It is possible to have a scenario that leads to the highest intake on Palcoma, while another scenario leads to the highest intake on Huayllara. Other control strategies are possible. Since 17 scenarios are defined and used in this simulation, the optimization results in a set containing 17 control actions for the intakes. Therefore, 17 possible control strategies exist, which are numbered from 1 to 17, where one corresponds to the most conservative strategy and 17 to the riskiest strategy.

Alternative control strategies

Besides the 17 control strategies described above, some other, less complex control strategies are possible; never use the intakes or always use the intakes. The first corresponds to not using the intakes of Palcoma and Huayllara at any moment. Only the Incachaca – Pampahasi pipeline is used to accomplish a good distribution of water between the Hampaturi and Incachaca reservoirs. The second correspond to using the intakes of Palcoma and Huayllara to always keep the reservoirs as full as possible. Only during situations in which the reservoirs are spilling, the intakes are not or less used.

3.2.2.4 Establishing the long-term simulation

A python script is built to use RTC-Tools to establish an MPC. It is chosen to use time steps of months during the simulation in accordance with RTC-Tools itself. In contrast to the scenarios also a 'base case' of precipitation data is needed which represents the 'real' precipitation during the simulation. The historical precipitation time series from the stations of Incachaca and Hampaturi over the period 2000 – 2016 will also be used for this base case to perform simulations with a length of 17 years. The MPC is established in such a way that the future precipitation of the base case is unknown and is predicted by the precipitation scenarios. In other words, the python script pretends that it does not know the future.

For each moment in time the three steps of MPC are applied: (1) the scenarios are used as prediction of future precipitation trajectories. (2) The water supply systems will be optimized for each scenario individually to determine their optimal control actions. The control strategy choses control actions based on these optimization results. (3) After application of the control actions the forecast horizon shifts ahead in time and the MPC can be continued with step (1). The structure of the python script to simulate the MPC is shown in Figure 12.

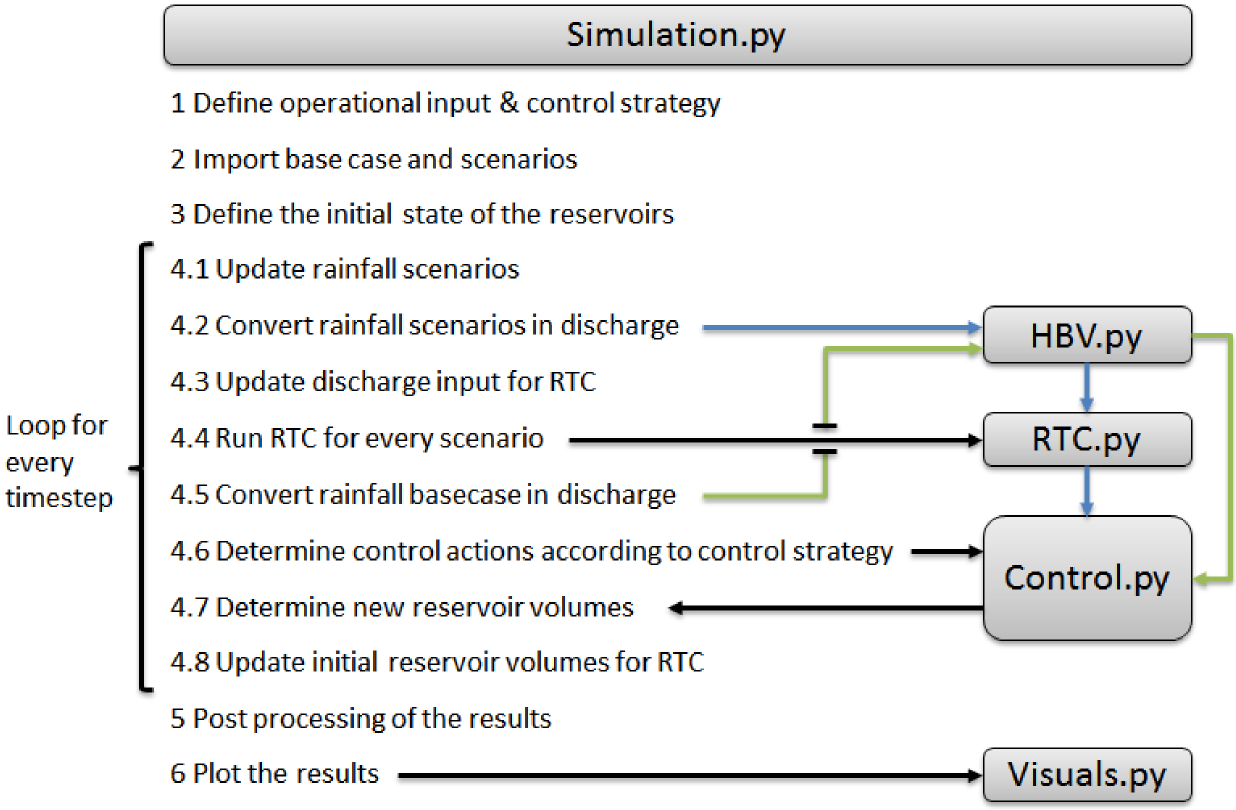

Figure 12: Schematization of the python script which simulates the MPC for the 2000 – 2016 period

At step 1 the operational input and the control strategy are defined. The operational input specifies the demands of the WTPs, the starting moment of the simulation, the length of the spin-up period, the length of the simulation, the time horizon of RTC-Tools and the number of scenarios. During step 2 the base case data and the scenarios are imported in Python from an Excel file. The 3rd step is to define the initial volumes of the reservoirs Incachaca and Hampaturi. Step 4 of the simulation contains a loop which simulates the MPC process for every time step. At 4.1 the correct period of two years is selected for the scenarios and the previous year of base case data is added as spin-up to establish the correct initial conditions for the HBV-models. Then at step 4.2 the scenarios are run in HBV on a daily basis and the resulting daily discharges are resampled to a monthly basis. At 4.3 these monthly discharge scenarios are used by RTC-Tools as input. RTC-Tools is activated at step 4.4 and the resulting set of optimized control actions is sent to the control script. The blue arrows in Figure 12 represent the data flow of the scenarios and their results.

After the scenario optimization, the 'real' discharges occurring at 'this moment' are calculated according to the base case precipitation by the HBV model at step 4.5 and consequently send to the control script, see the green arrows in Figure 12. Then at 4.6 the control actions are determined in the control script according to the prespecified control strategy and the output of RTC-Tools, see appendix A5 for an explanation of the control script. Subsequently at 4.7, the new reservoir volumes are calculated using the 'real' inflow discharges and the final control actions. These reservoir volumes are saved as the initial state for the optimization of the next timestep at step 4.8. Now the forecast horizon can shift one timestep ahead and the simulation continues at step 4.1. After the simulation is finished the post processing takes place at step 5, which calculates the costs of using the intakes and the total water shortages.

Reference situation

The entire base case of precipitation data is put into the HBV-models and is subsequently optimized by RTC-Tools, without establishing an MPC. The corresponding results show how the most optimal operational control over the 2000 – 2016 period would look like and what the associated costs and shortages would be. This operational control is unrealistic as it corresponds to a situation where the operator has perfect knowledge about the future natural conditions. However, these results can be helpful to place the results from the control strategies into perspective and determine the effect of the uncertainty of future precipitation.

3.2.2.5 Sensitivity of control strategies to the reservoir volumes

The sensitivity between the control strategies and the reservoir volumes is presented by plotting the long-term simulation results for all the individual months during the wet season; November, December, January, February, March and April. The stored volume of water in the reservoirs Incachaca and Hampaturi are summed for every timestep. The intake discharges of Palcoma and Huayllara are summed for every timestep as well and plotted together with the summed reservoir volumes.

3.2.2.6 Trade-off between water shortages and operational costs

To investigate the trade-off between water shortages and operational costs for the long-term simulation, it is executed using the 2018 WTP demands. To see how this trade-off changes in the future, the long-term simulation will also be executed for the projected WTP demands of 2022 and 2027, see Table 13 for these projections. It is important to note that during the long-term simulations the social constraint at Palcoma will not change, so the potential intake remains at 35%. To indicate the impact of changing the social constraint, some additional simulations are performed based on alternative potential intakes.

Table 13: Projections of WTP demands (EPSAS, 2014c)

WTP demands	
2018	
Pampahasi	0.647 m^3/s
Chuquiaguillo	0.208 m^3/s
2022	
Pampahasi	0.699 m^3/s
Chuquiaguillo	0.224 m^3/s
2027	
Pampahasi	0.804 m^3/s
Chuquiaguillo	0.245 m^3/s

4 Results

This chapter of the report presents all the results generated by the methods.

4.1 Rainfall - runoff modelling

The results from the rainfall - runoff modelling are presented in the following order; the data requirements, the sensitivity analysis and finally the model calibration and validation.

4.1.1 Data requirements

Figure 13 displays the PET for an average year, see appendix A2 for a description of the calculation process.

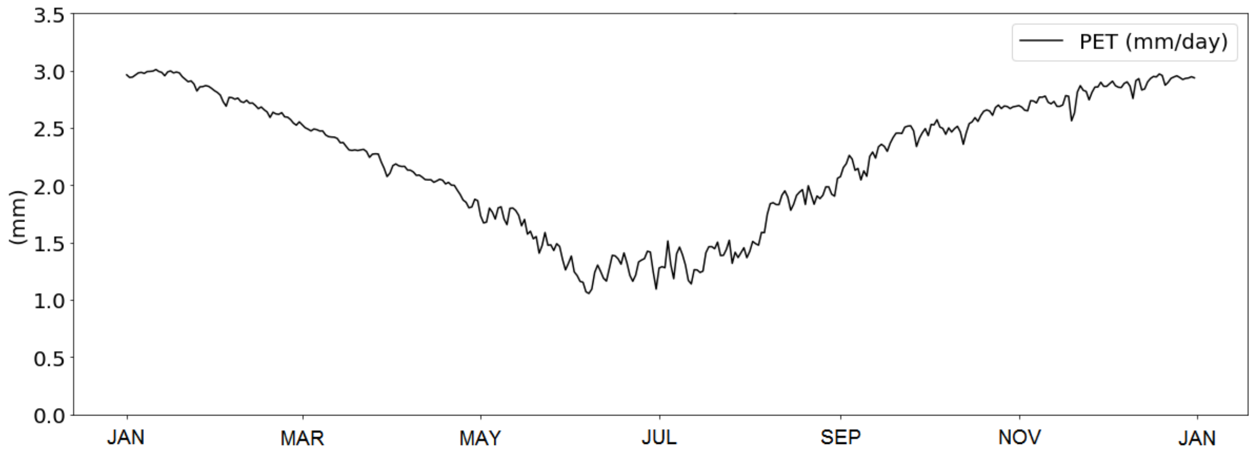

Figure 13: Annual variation of the calculated PET averaged over the period 2013 – 2016 with lapse rate 0.0125 ◦C/m

The discharge timeseries resulting from the reservoir balance of Incachaca and Hampaturi is plotted together with their respective precipitation data, see Figure 14 and Figure 15. The discharge timeseries of Incachaca is corrected for the unmonitored upstream reservoirs according to appendix A3. The precipitation time series of both Incachaca and Hampaturi are corrected using lapse rates according to appendix A1.

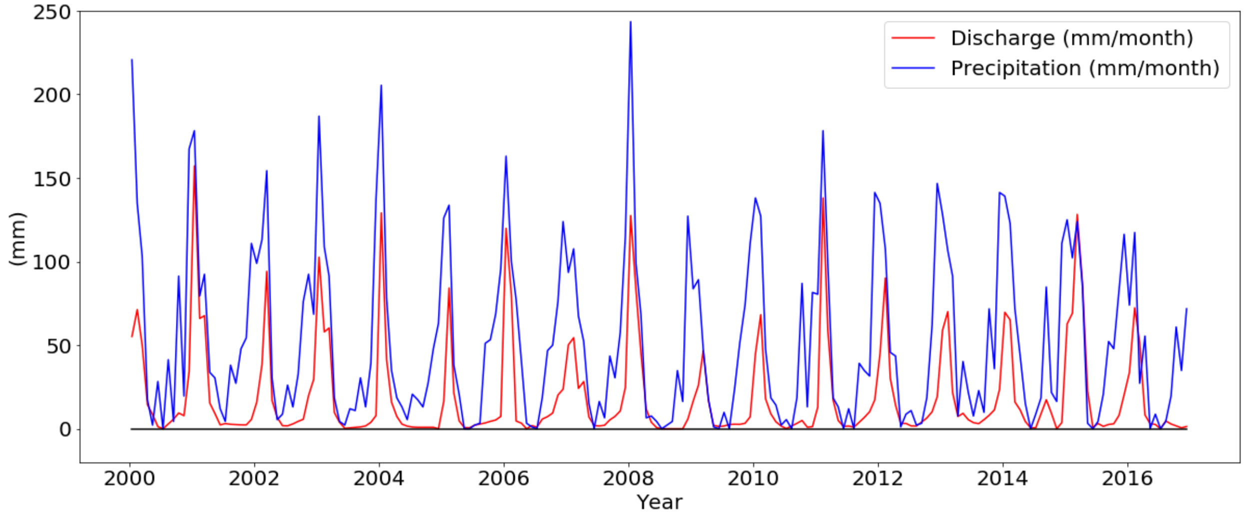

Figure 14: Discharge and precipitation for Incachaca (2000 – 2016), precipitation is measured at reservoir Incachaca

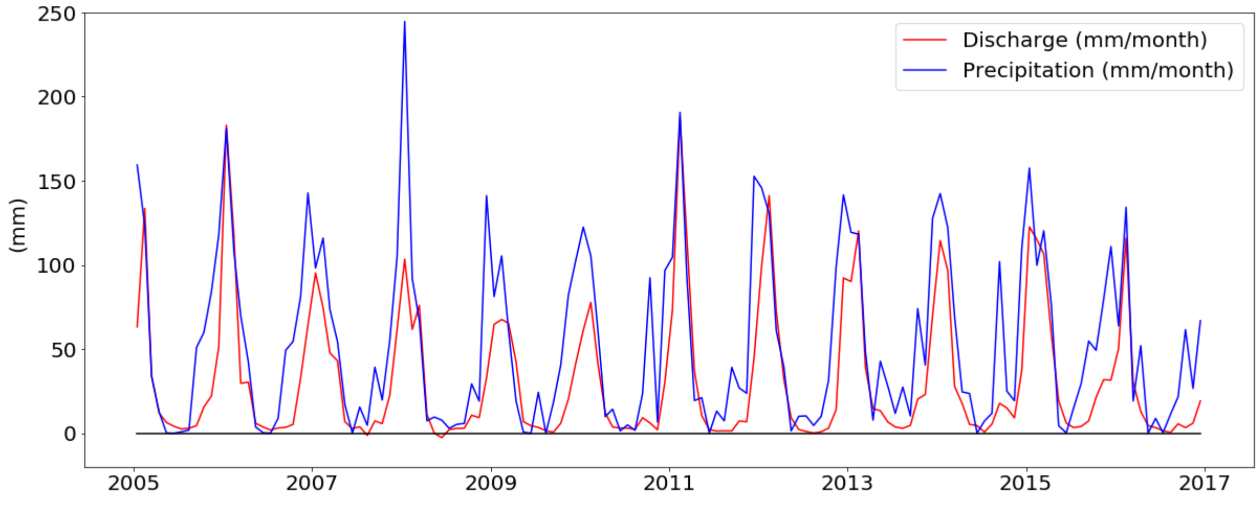

Figure 15: Discharge and precipitation for Hampaturi (2005 – 2016), precipitation is measured at reservoir Hampaturi Bajo

The differences in discharge between Incachaca and Hampaturi are remarkable. Incachaca responds later to precipitation in comparison to Hampaturi, see appendix A8 for a more detailed comparison. Furthermore, the relative discharge of Incachaca is also lower, indicating that Incachaca is more prone to evapotranspiration compared to Hampaturi. This is probably caused by differences in storage effects. See appendix A4 for an estimation of catchment-scale evapotranspiration, calculated based on a catchment water balance.

4.1.2 Sensitivity analysis

The results of the sensitivity analysis are presented in Figure 16 and Figure 17. NS and RVE are most sensitive to LP, FC and beta and somewhat sensitive to Perc and K4. The performance indicators are both not sensitive to alpha, kf and CFlux at all. In Figure 16, the line representing alpha is not observable because it is nearly identical to the line representing kf. Another remark should be made considering the lines representing LP. Since the starting value of LP was 0.75 and the parameter is physically limited to 1, the lines are cut off after a scaled value 1.33.

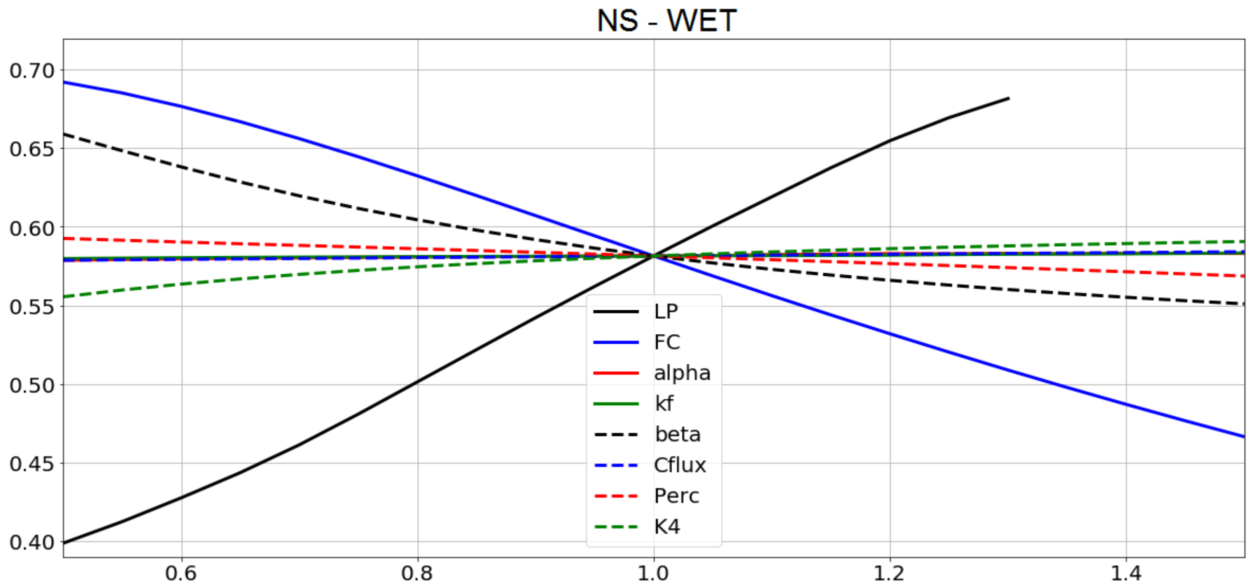

Figure 16: Sensitivity of the NS performance indicator to the model parameters

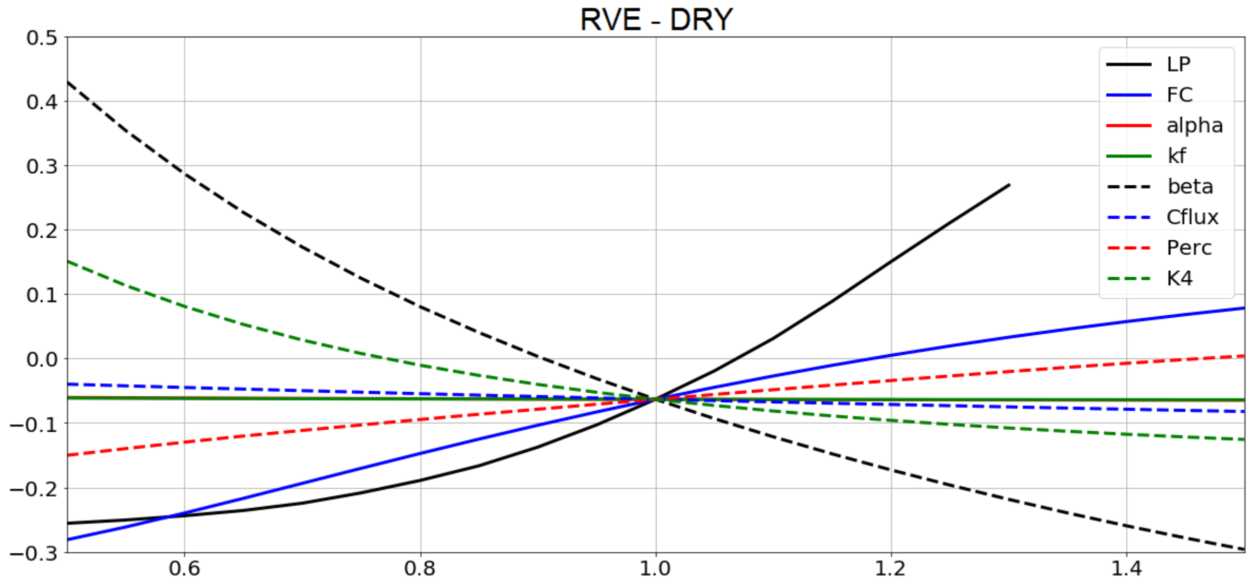

Figure 17: Sensitivity of the RVE performance indicator to the model parameters

The lack of sensitivity of alpha and kf to the model performance is probably caused by the upper storage zone which is completely empty most time steps. Another reason is that the model is calibrated and validated on a monthly basis, which minimizes the importance of an accurate quick runoff and makes the base flow more important. See Figure 18 and Figure 19 for the quick runoff (Quz) and base flow (Qlz).

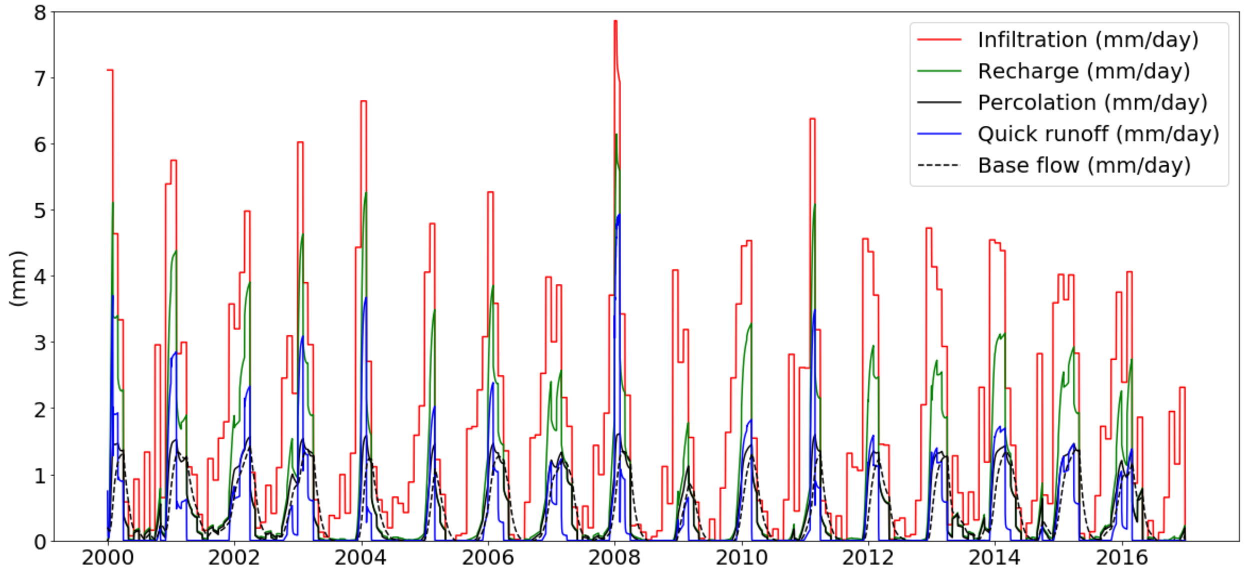

Figure 18: Important HBV-model fluxes, plotted for the Incachaca basin (2000 – 2016)

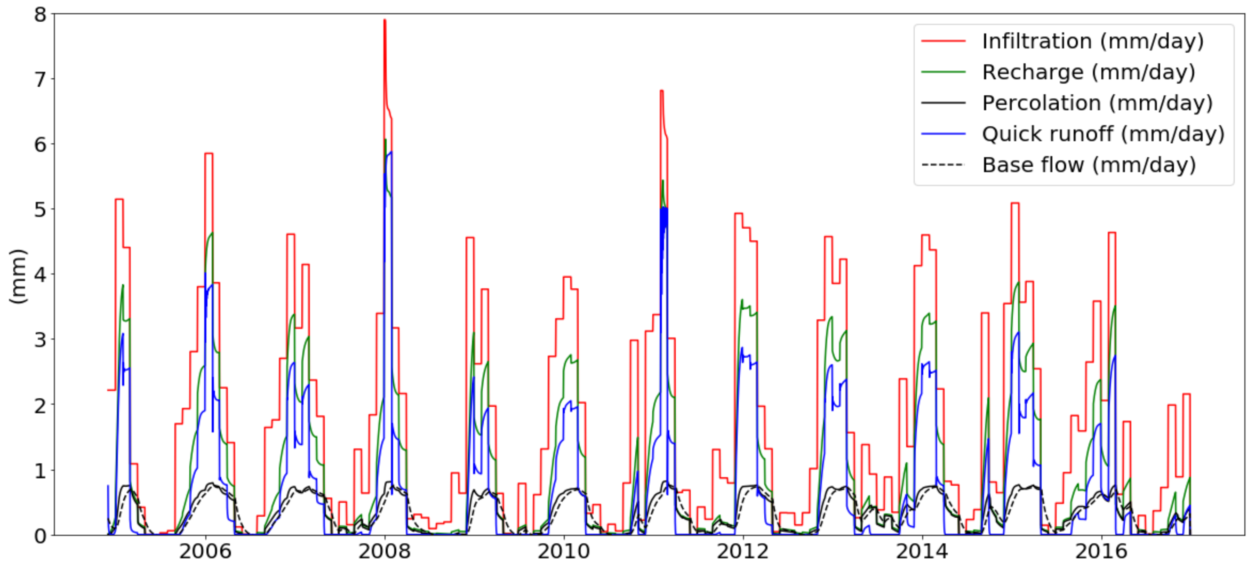

Figure 19: Important HBV-model fluxes, plotted for the Hampaturi basin (2005 – 2016)

The quick runoff is not very variable in comparison to the base flow, which is caused by the monthly calibration. Because, in this case the direct runoff is always zero, the infiltration is equal to the precipitation. At Incachaca the base flow has a greater contribution to the total runoff in comparison to Hampaturi, where the quick runoff contributes more to the total runoff.

4.1.3 Calibration and validation

The results regarding the calibration and validation of Incachaca are presented in Table 14. According to the results of the sensitivity analysis, it is decided to calibrate the models using the parameters LP, FC, beta, Perc and K4. Furthermore, it is decided to evaluate the model performance during the wet season using NS, since the shape and timing of the discharge peaks are considered more important than the total volume. During the dry season the model performance is evaluated using RVE, because during this season the total volume of discharge is considered more important than the variability of it. During the calibration, an RVE smaller than 5% is regarded sufficient, while NS should be closest to 1 as possible.

Table 14: Calibrated and validated HBV-model of the Incachaca basin

Calibrated model parameters					**Calibration**		**Validation**	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS	RVE [%]	NS
0. 45	200	4	2	0.07	4.76	0.8267	-13.29	0.7387

The validation results in a smaller NS than the calibration, which is as expected. The calibration and validation results of Hampaturi are presented in Table 15.

Table 15: Calibrated and validated HBV-model of the Hampaturi basin

Calibrated model parameters					**Calibration**		**Validation**	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS	RVE [%]	NS
Including outlier 2007/2008								
0.7	80	1.5	10	0.09	-3.19	0.7310	18.57	0.7450
Excluding outlier 2007/2008								
0.8	80	1.5	9	0.095	4.11	0.7803	30.12	0.7671

The calibration of the HBV-model including the outlier of 2007/2008 results in a lower NS than the validation does, which is unexpected. However, the calibration excluding the outlier results in a higher NS than the validation. Excluding the outlier of 2007/2008 results in a better model performance and less underestimation of the other wet periods. Calibration of the entire time series results in model parameters and RVE and NS as presented in Table 16 and Table 17 for Incachaca and Hampaturi respectively.

Table 16: Calibrated HBV-model of the Incachaca basin

Calibrated model parameters					**Calibration**	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS
0.45	180	5.5	2	0.04	1.99	0.7943

Table 17: Calibrated HBV-model of the Hampaturi basin

Calibrated model parameters					**Calibration**	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS
Including outlier 2007/2008						
0.8	80	2	18	0.115	0.14	0.7679
Excluding outlier 2007/2008						
0.95	100	2	9	0.12	3.26	0.7971

The model performance of Hampaturi is clearly increasing by excluding the outlier of 2007/2008. Figure 20 and Figure 21 display the observed and simulated discharges of Incachaca and Hampaturi.

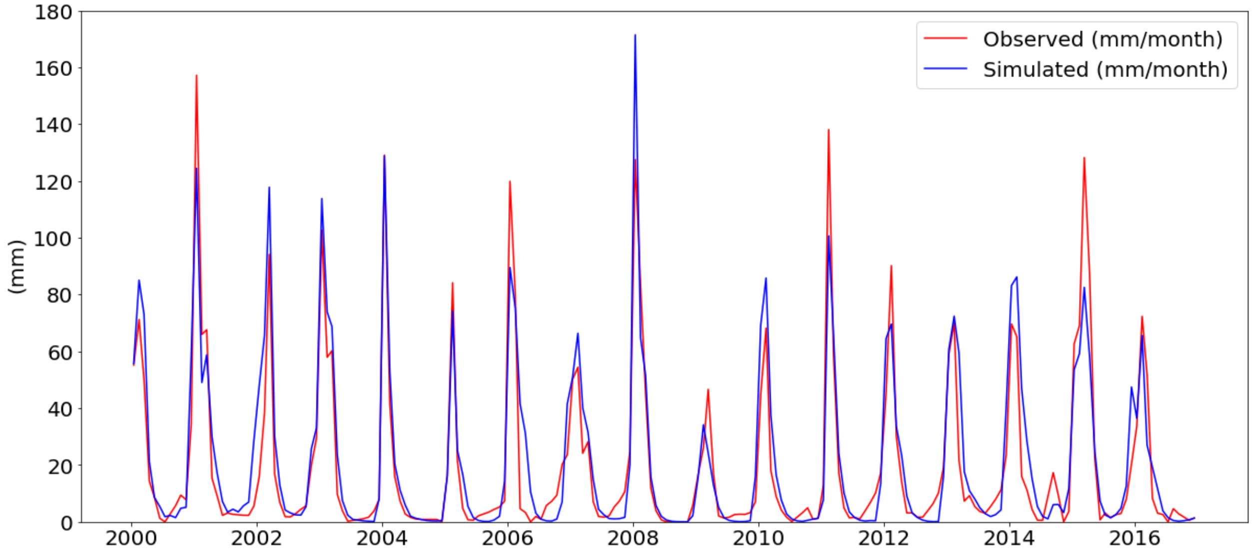

Figure 20 Hydrograph for the Incachaca basin showing simulated and observed discharges, calibrated using 2000 – 2016 period

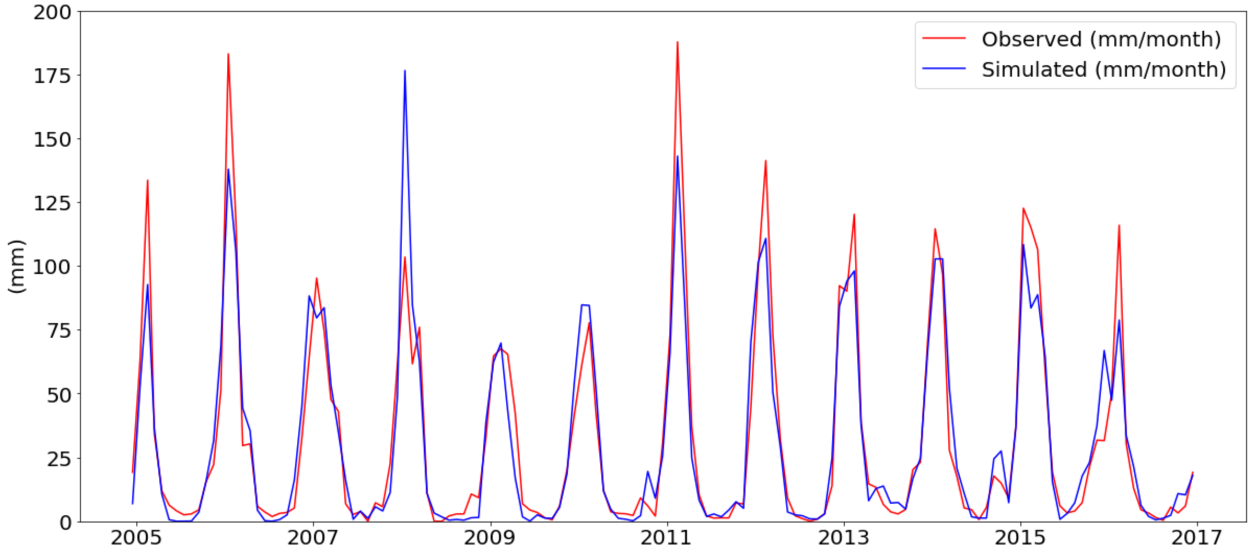

Figure 21: Hydrograph for the Hampaturi basin showing simulated and observed discharges, calibrated using 2005 – 2016 period (excluding outlier of 2007/2008)

Concerning the hydrological boundary conditions used in the optimization process, the main goal of the HBV-models is to predict the runoff during the wet season correctly. The focus is to simulate the timing and the shape of the peak discharge as good as possible, whereas the volume is of less importance, since during most years the reservoirs within the catchments of Incacahca and Hampaturi are spilling. According to Figure 20 the performance of the HBV-model of Incachaca is good with an accurate simulation of the interannual variability. Figure 21 shows the performance of the HBV-model representing the Hampaturi catchment, which also appears to simulate the interannual variability accurately. Although nearly every discharge peak is underestimated, this will probably not have a major impact on the optimization process, because the years with the smallest runoff (2009 & 2010) are not (very) underestimated.

4.2 Long-term simulation and decision support on real-time control

The results of the long-term simulation and the decision support on real-time control are presented in this section. First the long-term simulation results regarding the different control strategies are presented, then the sensitivity of the control strategies to the reservoir volumes is displayed and finally the trade-off between water shortages and operational costs is shown for different control strategies and future projections.

4.2.1 Simulation results of control strategies

To indicate the effects of the control strategies on the water supply system, the control actions belonging to different control strategies and the resulting reservoir volumes are displayed. First the control actions based on the 'perfect forecast' is presented in Figure 22. The upper subfigure presents the stored volume of the Hampaturi and Incachaca reservoirs over the total simulation length, the central subfigure presents the supply to WTP Pampahasi, the potential intake at Palcoma as constraint by the downstream requirements and the real intake following from the control action at Palcoma. The lower subfigure presents the supply to WTP Chuquiaguillo and the potential intake and control action on intake Huayllara.

As described in section 3.2.2.3, besides the 'perfect forecast', 17 control strategies are defined and used in the simulation which are numbered from 1 to 17, where one corresponds to the most conservative strategy and 17 to the riskiest strategy. Conservative is in this case defined as using the intakes considerably to reduce the chance of having shortages as much as possible. However, a conservative control strategy is also expensive. A risky control strategy takes in less water and is cheaper but allows a greater chance of having water shortages.

The control strategies 1, 2 and 3 are presented in Figure 23, Figure 24 and Figure 25 respectively. It is chosen to display control strategies 1, 2 and 3 because these are probably the most interesting control strategies for the decision maker to consider. Besides, these strategies show some clear differences in intake volumes and reservoir volumes compared to the riskier strategies. To indicate the behaviour of a riskier control strategy, control strategy 10 is presented in Figure 26. This strategy is presented because its control actions are clearly observable, whereas riskier strategies lead to very minimal intake volumes.

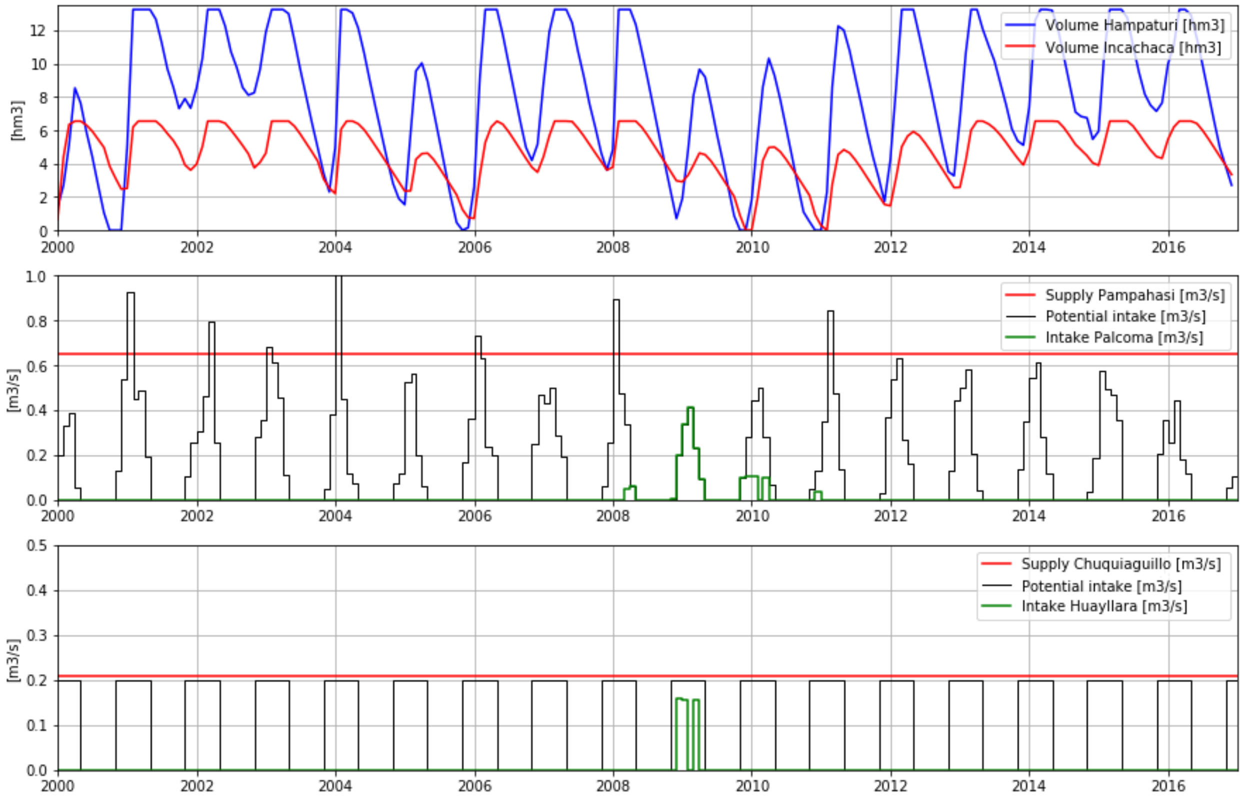

Figure 22: Long-term simulation results representing the situation in which the decision-maker has perfect future knowledge

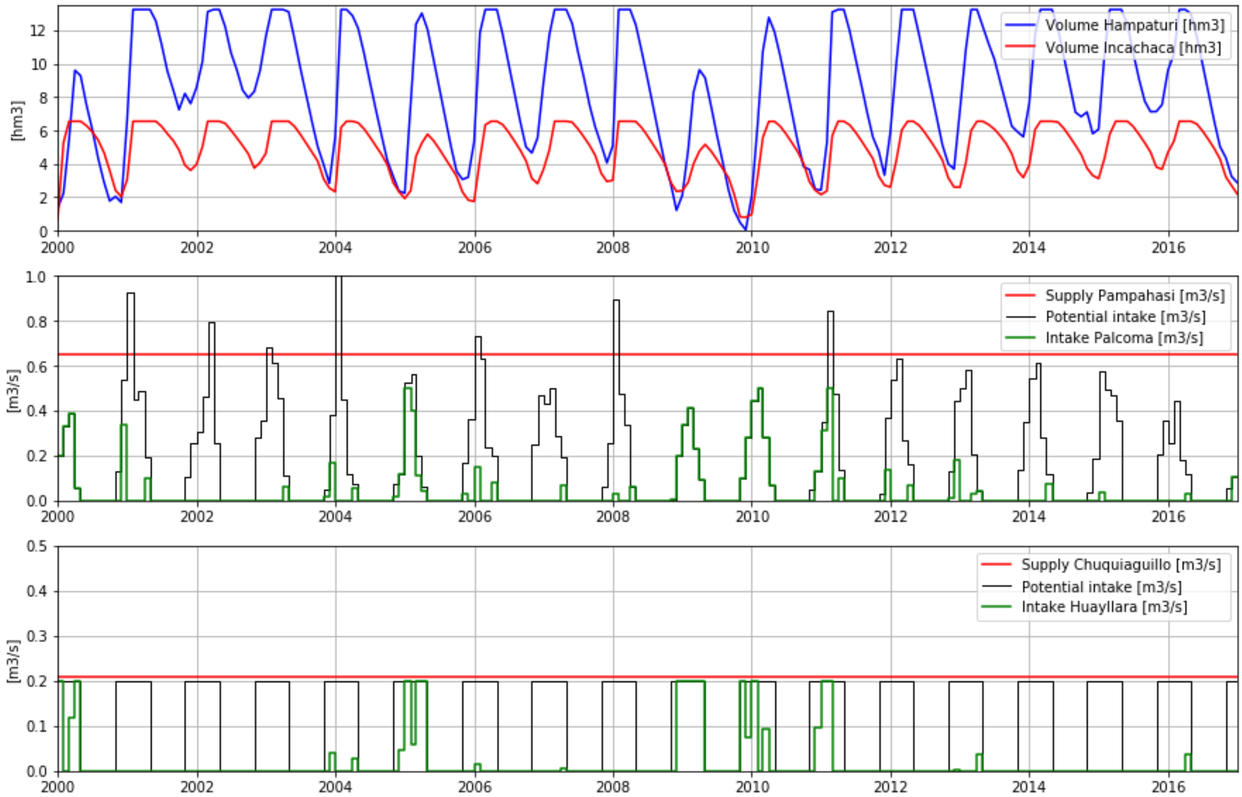

Figure 23: Long-term simulation results representing the most conservative control strategy, control strategy 1

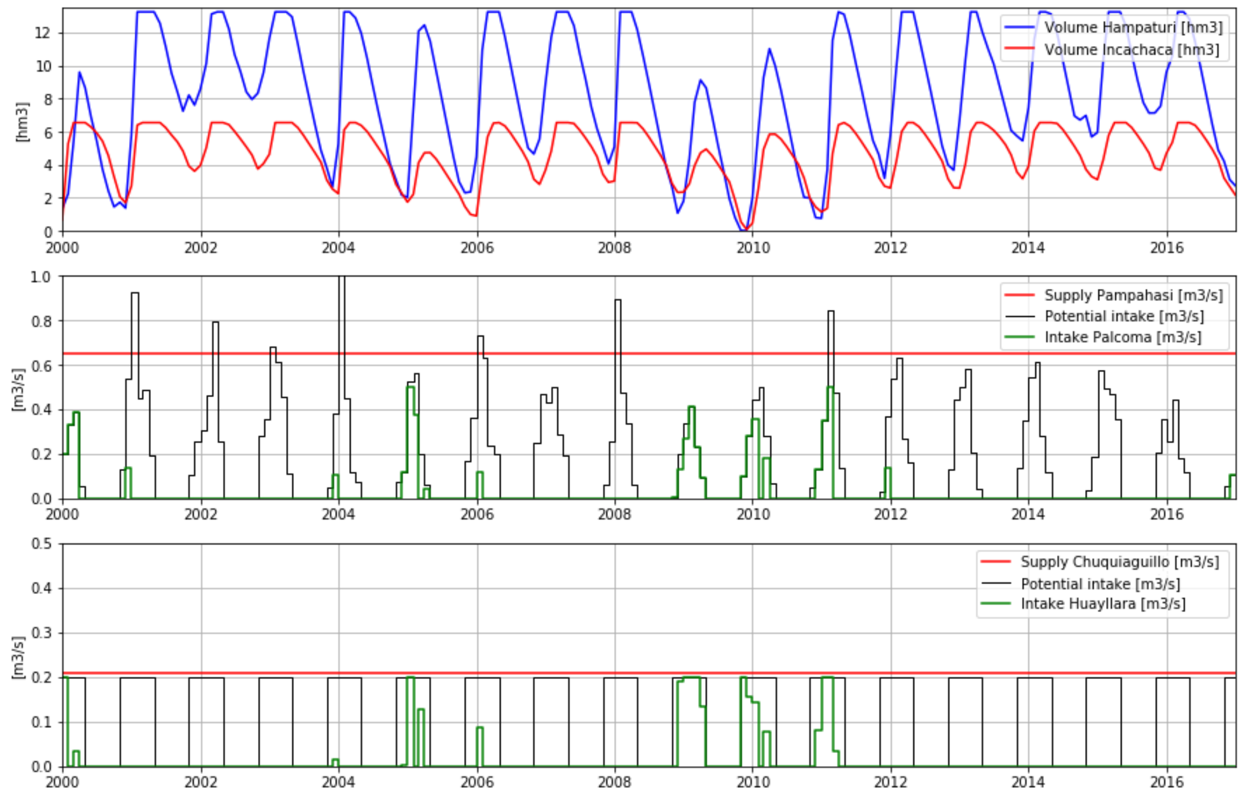

Figure 24: Long-term simulation results representing control strategy 2

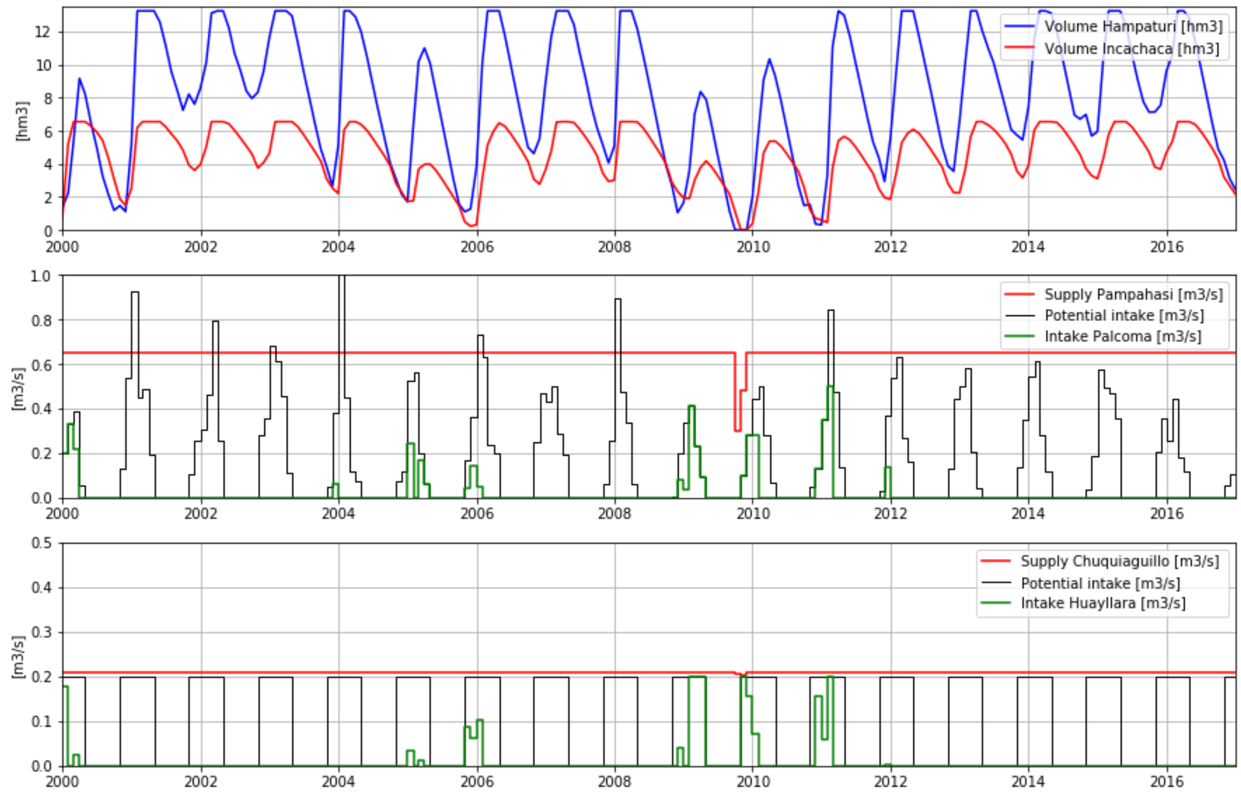

Figure 25: Long-term simulation results representing control strategy 3

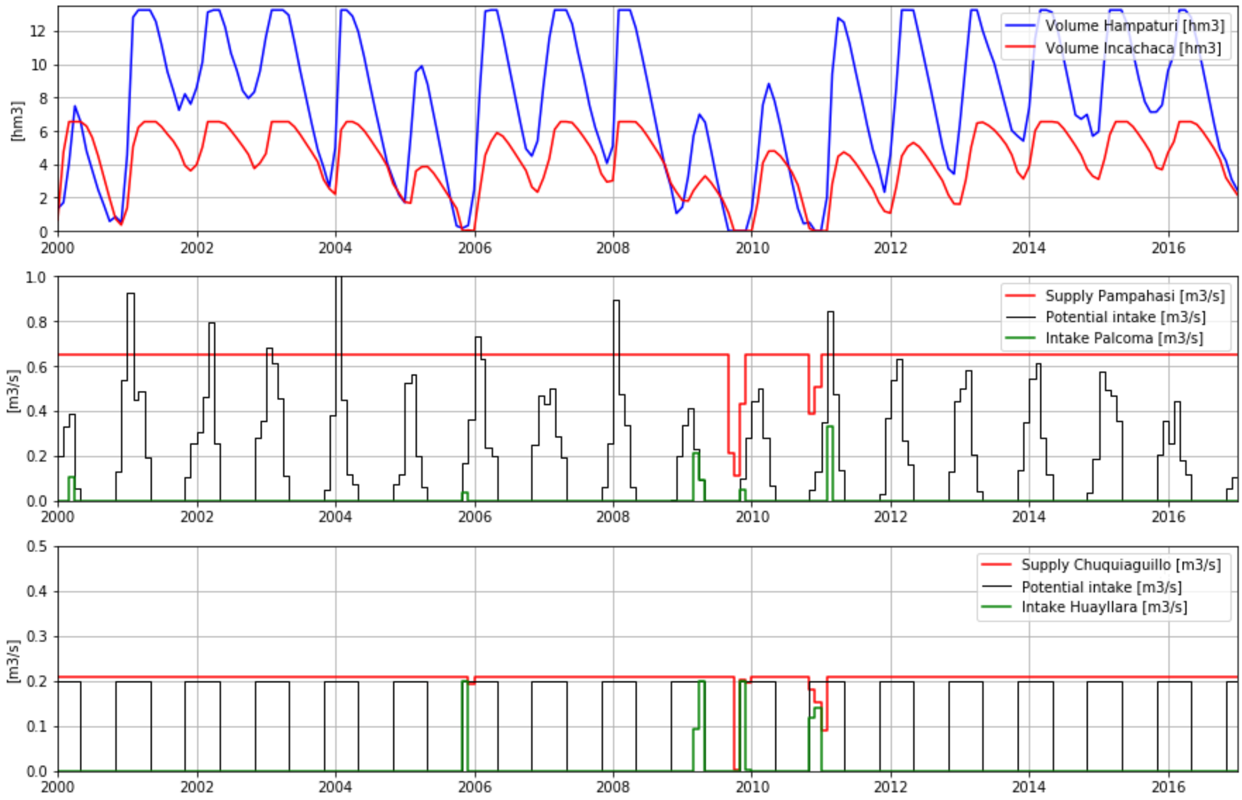

Figure 26: Long-term simulation results representing control strategy 10

The most optimal control strategy based on the 'perfect forecast' as presented in Figure 22 indicate what control actions are required to prevent water shortages at minimal costs. By comparing this to other control strategies it becomes clear what the impact of future uncertainty can be on the control actions and how much use of the intakes is unnecessary. The above figures clearly show that the years 2009 and 2010 are problematic having low reservoir volumes. Therefore, the most conservative control strategy, strategy 1, uses the entire potential intake of Palcoma during 2009 and 2010. Also, Huayllara takes in a lot of water during that period. As a result of these high intake volumes there are no water shortages at the WTPs when using control strategy 1. Control strategy 2 and 3 clearly take less water in at Palcoma and Huayllara, however for control strategy 3 this results in water shortages.

4.2.2 Trade-off between water shortages and operational costs

The trade-off between water shortages and operational costs for the WTP demands of 2018, 2022 and 2027 are displayed in Figure 27, Figure 28 and Figure 29 respectively.

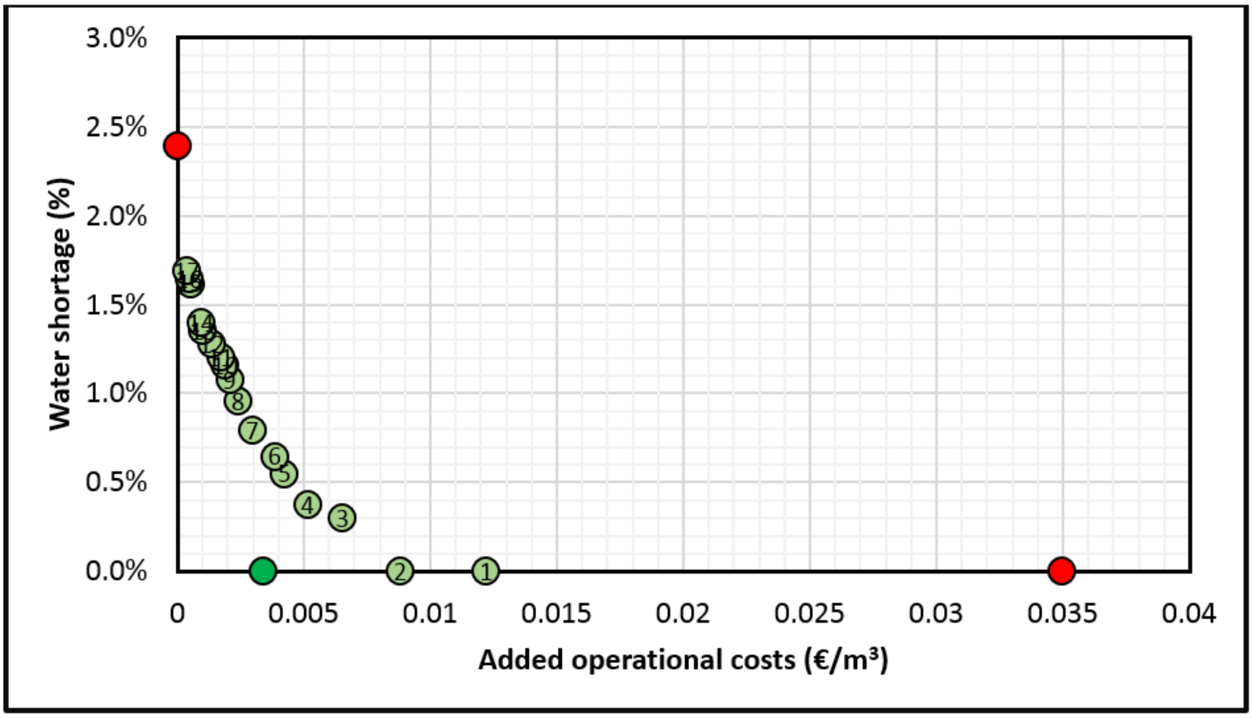

Figure 27: The trade-off between water shortage and operational costs during the 2000 – 2016 period for the WTP demands of 2018

Note that it concerns the relative water shortages, expressed as a percentage of the total demand over the entire 17 years. The added operational costs only concern the extra operational costs that are associated with using the intakes, other operational costs are disregarded. These added costs are divided by the total amount of water delivered to the WTPs, which is expressed as the total demand over the 17 years minus the total shortages over the 17 years.

The red dots represent the situations with no intake at all or the maximum intake. The maximum intake corresponds to using the intakes of Palcoma and Huayllara to always keep the reservoirs as full as possible. Only during situations in which the reservoirs are spilling, the intakes are not or less used. The light green dots correspond to the different intake strategies, 1 is the strategy that is most conservative, 2 is a bit less conservative, etc. The green dot is the most optimal strategy which represents the situation in which the decision-maker has perfect knowledge about future inflows. Control strategy 1 and 2 both manage to have zero shortages, at an added cost of around 0.01 € for every used m^3 of water. So, in that case the water users will pay an extra 0.01 € for every m^3 they use. For control strategy 5 and higher the shortages increase quickly, while the costs do not decrease very quickly.

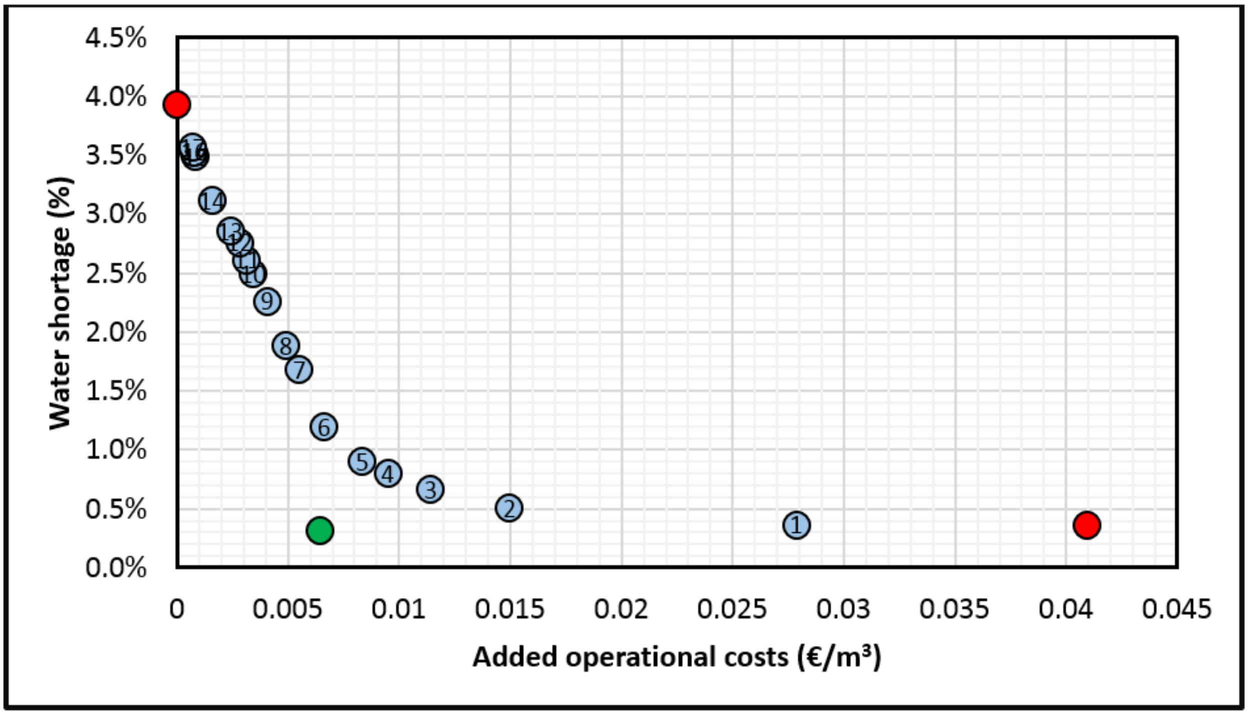

Figure 28: The trade-off between water shortage and operational costs during the 2000 – 2016 period for the WTP demands of 2022

Figure 28 presents the trade-off for the WTP demands of 2022. Apperently, there is no control strategy which can reduce the water shortages to zero. Even the maximum intake strategy results in a shortage of about 0.4%. This indicates that the ability of the infrastructure to store and supply water to the WTPs is inadequate.

It should be noticed that the green dot representing the optimal intake strategy has a smaller total water shortage than the maximum intake or intake strategy 1. While, the maximum intake strategy does already take the maximum amount of water in before and during the occurring shortage. This difference is caused by the incorrect representation of the losses on the Incachaca – Pampahasi channel in the Modelica model as explained in section 3.2.1.3.

Within the optimal intake strategy, determined directly by RTC-Tools, this results in a slightly smaller loss and a smaller corresponding water shortage. During the long-term simulations of the control strategies the RTC-Tools results are only used to determine the control actions on the intakes, while the channel losses are included correctly in the control script, as explained in Figure 38 in appendix A5. For the 2022 simulation this incorrect loss representation amounts to 220,000 m^3 as can be seen in Table 19 by the two yellow-marked numbers.

A check on the use of the Incachaca – Pampahasi channel before and during the occurring water shortage proves that if a loss of 10% was applied instead of 2.3% an extra amount of 200,000 m^3 would be lost. The incorrect implementation of the channel losses will also influence the operational costs of the optimal strategy, because more losses on the Incachaca – Pampahasi channel will in some cases lead to more intake to compensate for this.

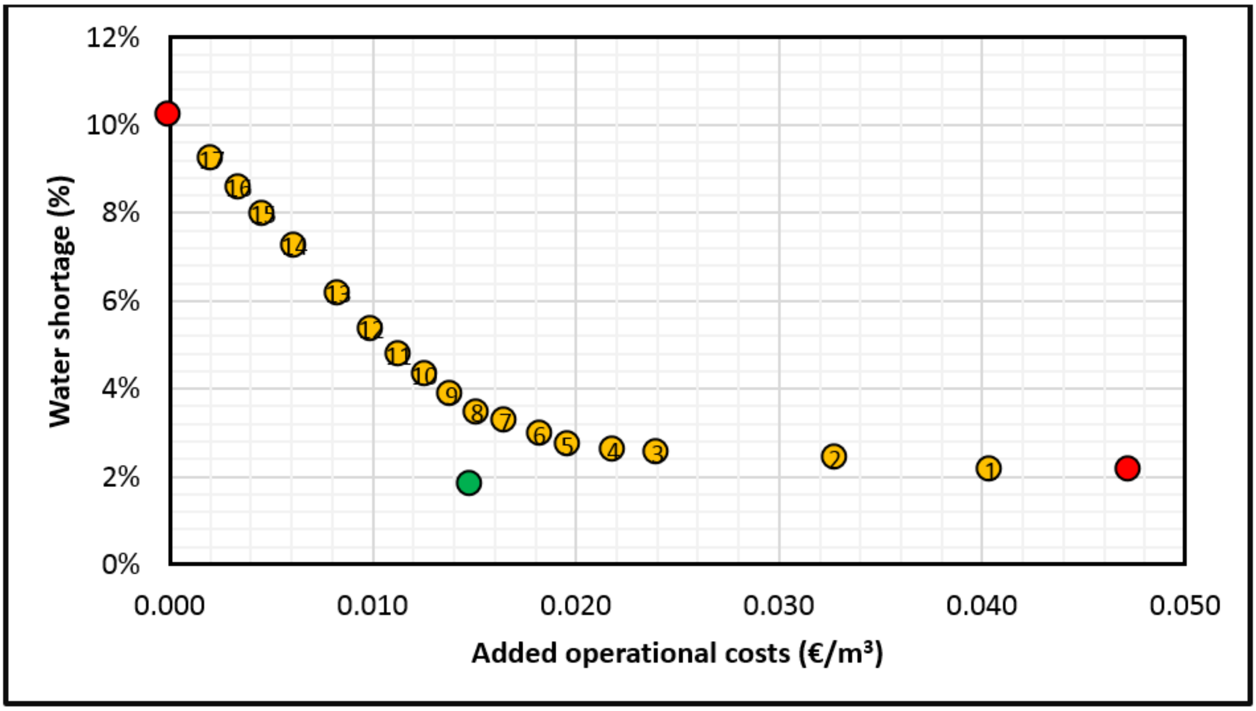

Figure 29: The trade-off between water shortage and operational costs during the 2000 – 2016 period for the WTP demands of 2027

Figure 29 presents the trade-off for the WTP demands of 2027. The minimal shortages that emerge in this situation are 2% of the total demand, which is considered as a lot. Because these shortages emerge on a few moments during the entire simulation period 2000 – 2016, the shortages can be severe and last multiple months. In 2027 the infrastructure is clearly inadequate in storing and suppling water to the WTPs. An added operational cost of 0.03 €/m^3 corresponds roughly to a total of 10^6 € annually. Figure 30 shows how the different (future) trade-offs relate to each other. The relative water shortages and added operational costs both clearly increase quickly as the WTP demands will increase from 2018 until 2027.

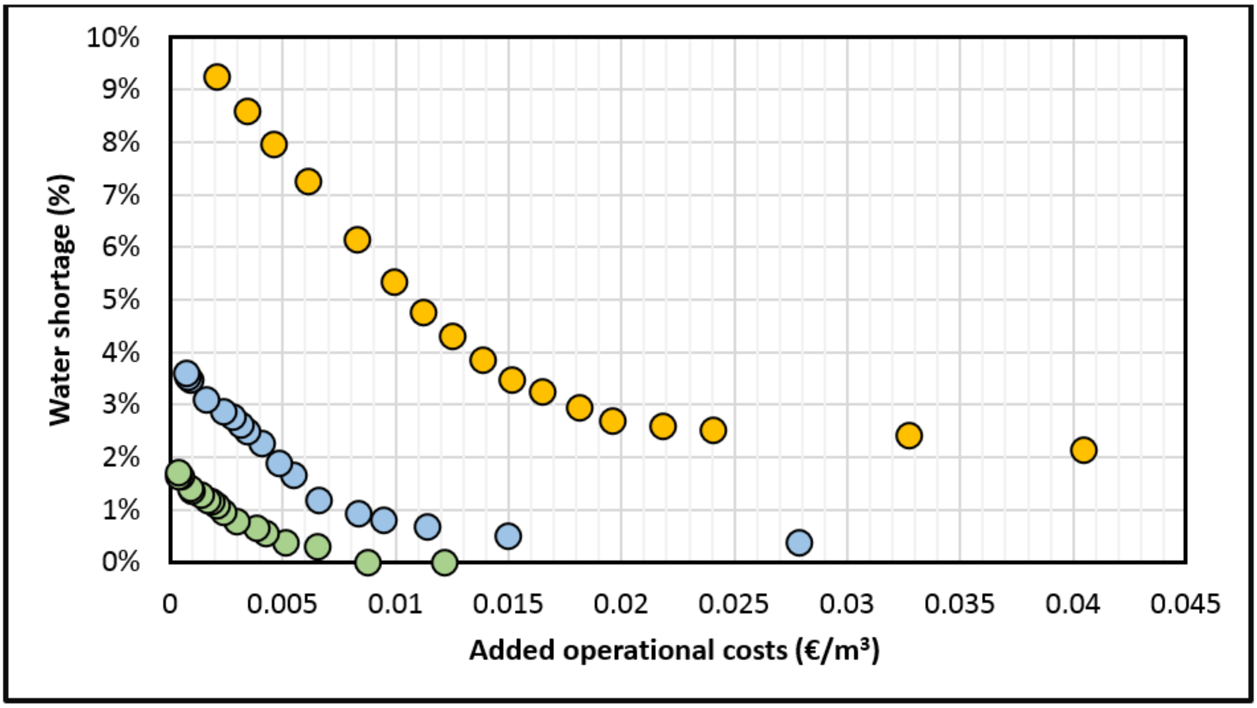

Figure 30: The trade-off between water shortage and operational costs during the 2000 – 2016 period for the WTP demands of 2018, 2022 and 2027

The numbers corresponding to the shortages of 2018 and 2022 displayed in the figures above are presented in Table 18 and Table 19. These tables also indicate the absolute water shortages over the 17-year period. Besides, the number of months and years experiencing shortages are displayed. Also, the distribution of the shortages among the two WTPs is presented by the columns ‘Pampahasi (%)’ and ‘Chuquiaguillo (%)’, showing the percentage of the occurring shortage which belong to Pampahasi and Chuquiaguillo respectively.

Table 18: The absolute and relative water shortages resulting from the long-term simulation based on the 2018 WTP demands

2018	**Shortage**					
	(10^6 m^3)	(%)	(Months)	(Years)	Pampahasi (%)	Chuquiaguillo(%)
Max intake	0	-	0	0	-	-
Strategy 1	0	-	0	0	-	-
Strategy 2	0	-	0	0	-	-
Strategy 3	1.37	0.30	2	1	99%	1%
Strategy 4	1.72	0.37	3	1	99%	1%
Strategy 5	2.53	0.55	5	2	97%	3%
Strategy 6	2.97	0.65	6	2	94%	6%
Strategy 7	3.64	0.79	6	2	87%	13%
Strategy 8	4.40	0.96	7	3	83%	17%
Strategy 9	4.95	1.08	8	3	80%	20%
Strategy 10	5.32	1.16	8	3	78%	22%
Strategy 11	5.51	1.20	8	3	78%	22%
Strategy 12	5.87	1.28	8	3	76%	24%
Strategy 13	6.21	1.35	9	3	75%	25%
Strategy 14	6.42	1.40	9	3	73%	27%
Strategy 15	7.43	1.62	10	3	69%	31%
Strategy 16	7.56	1.65	10	3	69%	31%
Strategy 17	7.75	1.69	10	3	68%	32%
No intake	10.97	2.39	10	3	39%	61%
Optimal intake	0	0	0	0	-	-

Table 19: The absolute and relative water shortages resulting from the long-term simulation based on the 2022 WTP demands

2022	Shortage					
	(10^6 m^3)	(%)	(Months)	(Years)	Pampahasi (%)	Chuquiaguillo (%)
Max intake	1.81	0.37	3	1	100%	0%
Strategy 1	1.81	0.37	3	1	100%	0%
Strategy 2	2.50	0.50	3	1	98%	2%
Strategy 3	3.31	0.67	3	1	96%	4%
Strategy 4	3.98	0.80	5	2	88%	12%
Strategy 5	4.49	0.91	5	2	84%	16%
Strategy 6	5.92	1.20	7	3	88%	12%
Strategy 7	8.34	1.68	11	3	88%	12%
Strategy 8	9.32	1.88	14	4	86%	14%
Strategy 9	11.20	2.26	16	4	80%	20%
Strategy 10	12.37	2.50	16	4	79%	21%
Strategy 11	12.94	2.61	16	4	79%	21%
Strategy 12	13.67	2.76	16	4	79%	21%
Strategy 13	14.17	2.86	16	4	79%	21%
Strategy 14	15.44	3.12	17	4	80%	20%
Strategy 15	17.27	3.49	17	4	77%	23%
Strategy 16	17.47	3.53	17	4	76%	24%
Strategy 17	17.68	3.57	17	4	76%	24%
No intake	19.46	3.93	17	4	72%	28%
Optimal intake	1.59	0.32	3	1	100%	0%

Changing the social constraint at Palcoma from 65% to 50% for the 2022 WTP demand, reduces the overall water shortages corresponding to strategy 1 from 1.81 * 10^6 to 0.6 * 10^6 m^3 of water. Since the potential intake at Palcoma is increased from 35% to 50%, a higher intake discharge is possible. More surprising is the effect on the operational costs, which are lowered from 13.74 * 10^6 € to 10.94 * 10^6 €, a reduction of 20%. This effect can be explained by the future uncertainty of available water. Due to lowering the social constraint, more water becomes available, which is especially important during the months November and December. Because within the scenarios extra water is available for the intakes, their corresponding control during the previous wet period can become more reactive. Leading to lower intake discharges during the months March and April. While the dry season progresses, the future uncertainty until the wet season resolves, leading to less unnecessary use of the intakes.

4.2.3 Response of control strategies to the reservoir volumes

To display the relationship between the behavior of the control strategies and the reservoir volumes, the intake discharge of the intakes Palcoma and Huayllara was added and plotted against the total reservoir volume of the reservoirs Incachaca and Hampaturi. See Figure 31 for the response of the first four control strategies to the reservoir volumes during the month January. Every point represents the total reservoir volume at the 1st of January and the corresponding total intake discharge during the month January. Since the simulation is performed over a time span of 17 years, each subfigure shows 17 points.

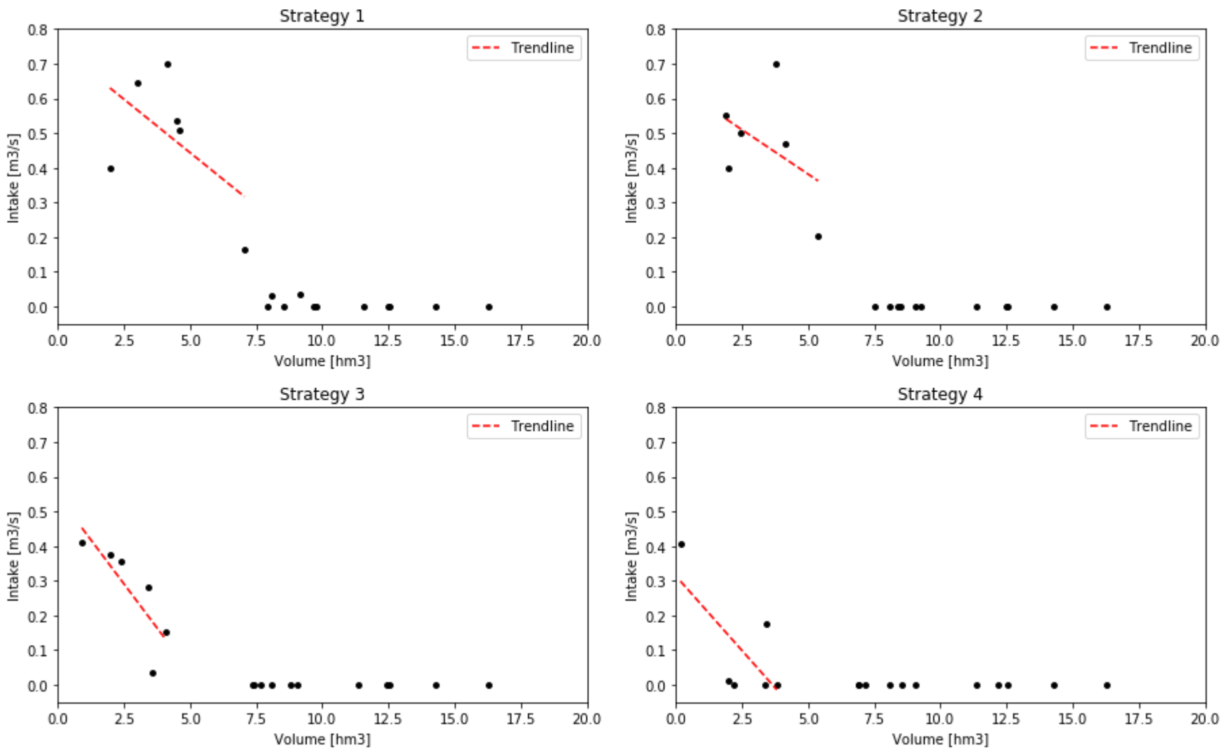

Figure 31: Total intake discharge plotted against the total stored volume for the month January for different control strategies

The results do not show a clear line or graph as one might expect. This is due to two reasons; varying initial hydrological conditions and a varying potential intake discharge at Palcoma. Wet initial hydrological conditions can lead to a much higher runoff compared to dry initial hydrological conditions, see appendix A5 for an analysis of this impact. Due to this variation in initial hydrological conditions, a low reservoir volume does not necessarily lead to high intake discharges. Besides, in some situations the control strategy suggests taking in a lot of water in response to low reservoir volumes, while this water is not available at the intake. This is only the case for intake Palcoma, since at intake Huayllara the assumption is made that a constant potential intake discharge is available.

Despite these shortcomings, the results still give a clear indication about the response of the control strategies to the reservoir volumes. Trendlines have been added to indicate how and at what reservoir volume the control strategies start to respond by using the intakes. It appears that if the control strategy becomes riskier its response becomes less intense. Besides, a more conservative strategy starts to respond already to higher reservoir volumes. Strategy 1 starts responding around 7.5 hm^3, while strategy 2, 3 and 4 start responding around 5.5 hm^3, 4 hm^3 and 3.5 hm^3 respectively.

The trendlines that are drawn in Figure 31 for the first four control strategies during the month January, are plotted in Figure 32 again to show how the response of the control strategies in January relate to the months December, February and March. The differences between the control strategies are clearly visible and their responses are consistent. Besides, the response clearly changes as the wet season progresses. Obviously, at the end of the wet season the reservoirs need to store enough water to last the entire dry season.

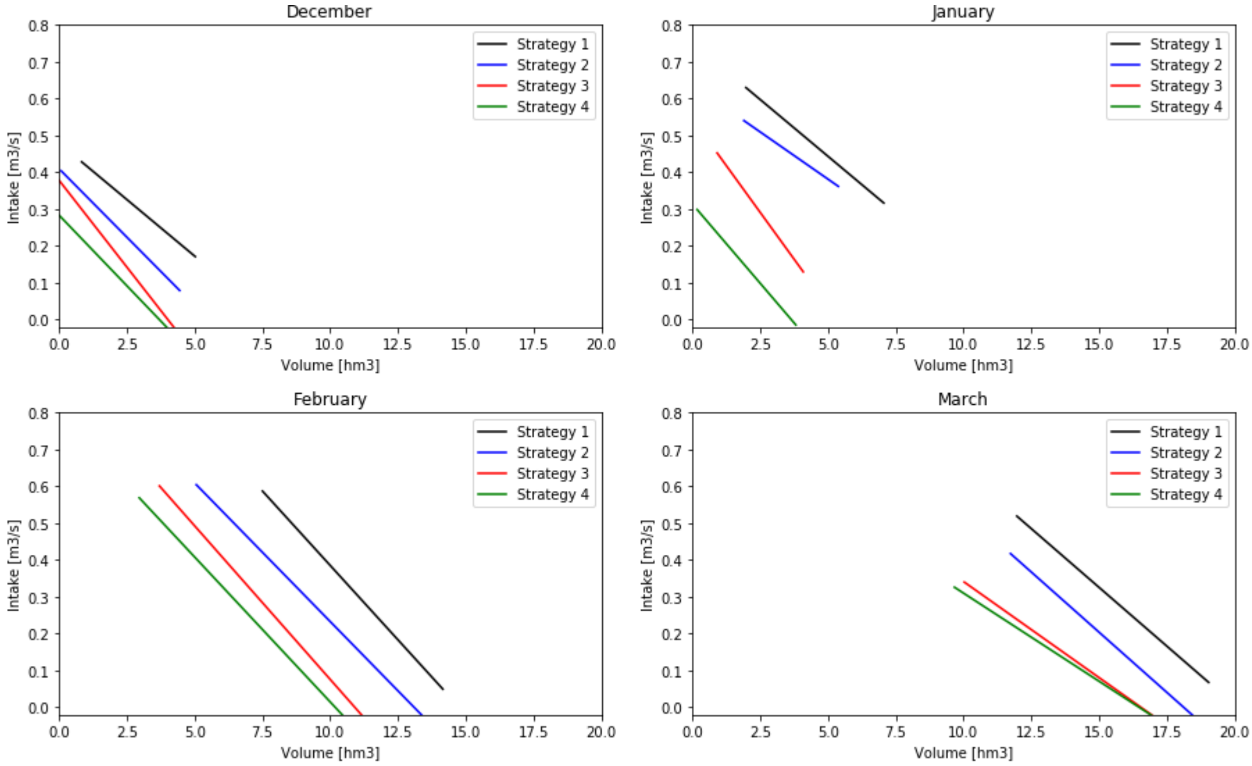

Figure 32: Trendlines representing the relation between intake discharge and stored volume for the first four control strategies for different months during the wet season

These results might be used as a simplified decision support to determine the control actions on the intakes based on the current month of the wet season, the preferred controls strategy and the stored volume of water. A shortcoming would be that this method omits the effect of the varying initial hydrological conditions on the expected future runoff.

5 Discussion

Every research involves decisions, assumptions and uncertainties regarding the used models, methods and data to generate results. This chapter of the report will reflect upon all the decisions and assumptions made during the execution of the research and discuss the impact of uncertainties on the results. First, the rainfall-runoff modelling is discussed and consequently the long-term simulation and decision support on real-time control.

5.1 Rainfall-runoff modelling

The available precipitation and temperature data introduce uncertainties impacting the rainfall-runoff modelling. The precipitation data is collected at different locations and altitudes than where it is applied, leading to uncertainties due to spatial variability and the orographic effect. Precipitation can vary greatly on short distances, possibly leading to major differences within the catchments. The orographic effect is included in the analysis by introducing a precipitation lapse rate based on multiple measurement stations. However, compared to other studies this precipitation lapse rate appears to be low. The uncertainty within the temperature data might be even larger, having less measurement stations and all being located outside the study area. The resulting temperature lapse rate is about two times higher compared to values from literature that apply to high altitude Andes regions.

However, the calculated PET values are little sensitive to the temperature lapse rate and show good agreement with values from the literature that apply to the Andes region. Since these PET values are used to give an indication about the seasonal variability, it is not necessary to have very accurate values. Despite precipitation and PET being direct input for the HBV-model, the model performance is good given the task in this study to model the rainfall-runoff on a monthly scale. The performance of the HBV-models is evaluated based on the model accuracy during the wet season and the dry season separately. The accuracy of the discharge predictions during the wet seasons is good. Most discharge peaks do not show large errors in volume, while the shape and timing of the peaks is accurate. The model of Hampaturi slightly underestimates most discharge peaks, but since these are mainly relative high peaks they still lead to spill at the Hampaturi reservoir. Calibration of the dry seasons using RVE results in an overall low volume error, however the variation of RVE between the different dry seasons is large. So, despite the low RVE values the model accuracy during the dry seasons is not that good. But, since the discharges during the dry season are low, the impact on the long-term simulation is small.

The quality of the discharge data used to calibrate and validate the HBV-models probably has the biggest impact on the model performance. Especially during the dry season there are errors. This discharge data is calculated according to the reservoir balances, based on water level, spill and outflow measurements. It is expected that the outflow measurements involve large uncertainties, as the technique used by EPSAS to measure the outflow is unclear. Furthermore, the reservoir water levels are translated using a water level/volume relationship which also introduce uncertainties.

Direct evaporation and rainfall were not explicitly included in the reservoir balance. However, since the direct evaporation and rainfall impact the measured reservoir volumes, these effects still impact the discharges resulting from the reservoir balance. Now these discharges represent the amount of water available for the WTPs instead of the exact amount of water that flows into the reservoirs. Since within RTC-Tools, these effects are also omitted, it is not considered as a major shortcoming of the methodology. Although, this approach makes it impossible to optimize the water release of the individual reservoirs to minimize reservoir evaporation losses.

5.2 Long-term simulation and decision support on real-time control

An important decision during the modelling of the real-time control process was the choice to aggregate all the physical reservoirs to one single virtual reservoir per catchment. Due to the limited data availability it was not possible to establish separate HBV-models for the individual reservoirs within the catchments. For Hampaturi it could have been decided to split the catchment in two HBV-models according to the reservoirs of Hampaturi Bajo and Ajuan Khota. The main reason not to do this is that the separated HBV-models perform worse compared to the model representing the entire Hampaturi catchment. Combining the individual reservoirs to single virtual reservoirs can lead to overestimating the ability of the catchments to store water. A situation in which downstream reservoirs are full, while an upstream reservoir is not can lead to spill, if precipitation would drain to a downstream reservoir. Using one combined virtual reservoir neglects such spill behaviour, which might lead to an underestimation of the simulated shortages and operational costs.

The scenarios used in the long-term simulation are limited to the 17 years of historical data. This yield risks, because a drier year can appear than was present during the 2000 – 2017 period, or dry years can occur more frequent. These effects were not studied in this research. Also, the impact of autocorrelations and seasonal forecasts on the operational control and trade-off between water shortages and operational costs was not included. It could be possible that autocorrelation patterns are present within the precipitation data which might help indicate persistent dry periods caused by climate oscillations like El Nino-La Nina. Seasonal forecasts could help indicating such climate oscillations and reduce future precipitation uncertainty.

The control on the Incachaca – Pampahasi channel is not directly based on the output of the scenario optimization, because the variation in precipitation between Incachaca and Hampaturi that can exist in the scenarios might lead to a discrepancy between the water distribution within the scenarios and the base case. Each time new information of inflows becomes available during the long-term simulation, the control action on the Incachaca – Pampahasi channel changes for every scenario. By following the scenario involving the largest use of the Incachaca – Pampahasi channel it is prevented that situations occur in which the channel is used too little. By consequently delaying the corresponding control actions to the end of the wet period as long as possible, unnecessary use of the channel can be reduced while new information becomes available. This also reduces the amount of losses involved with using the channel. According to the long-term simulation results this control works properly.

Another decision impacting the results is the method used to optimize the control actions. Within RTC-Tools the decision was made to use the sequential programming method to prioritize the optimization process according to a clear hierarchy. It was decided to prioritize the supply to the WTPs over minimizing the operational costs, which results in control actions that does not lead to a trade-off between water shortages and operational costs. However, by introducing scenarios the uncertainty of future precipitation is added to the optimization problem, which inevitably leads to a trade-off between water shortages and operational costs. Therefore, this decision has no effect on the long term simulation results.

Furthermore, it is questionable whether the decision to prioritize the water supply to WTP Chuquiaguillo over the supply to WTP Pampahasi impacted the long term simulation results. Water shortages occur more often at WTP Pampahasi, especially for conservative control strategies. However, this effect is mainly caused by the control on the Incachaca – Pampahasi channel. As described above, the use of the Incachaca – Pampahasi channel is minimized within the control script as much as possible to prevent unnecessary channel losses. Despite that the minimization of the Huayllara intake was prioritized over the minimization of the Palcoma intake, on many moments during the simulation both are used to their full potential, especially during the months preceding shortages. If the optimization leads to different intake discharges, the effect on the long term simulation results is probably still small, because the control strategies do not necessarily lead to control actions for Huayllara and Palcoma belonging to the same optimized scenario. Another difference between RTC-Tools and the control script is the distribution of occurring water shortages. RTC-Tools distributes a shortage over time as good as possible, while in the control script a shortage is not distributed and can lead to intense shortages. However, the goal of this study did not include early warning or mitigation of water shortages.

Within the optimization methodology it is assumed that at intake Huayllara always 0.2 m^3/s is available to take in during the wet season. This assumption is based on a hydrological study from EPSAS on the discharge of the river feeding the Huayllara intake. It is unknown what the uncertainty is regarding this analysis and how often the 0.2 m^3/s is not available. Another important choice was to model the discharge of the Palcoma River with an HBV-model using the same precipitation data and calibration settings as the Hampaturi model. Although, the precipitation data was corrected for the elevation of the Palcoma catchment, it is very questionable whether this HBV-model is an accurate predictor of Palcoma's hydrological behavior. Furthermore, according to EPSAS only about 35% of the flow at Palcoma is available for the intake in 2018 due to social reasons. But, it is questionable if it is possible to take in 35% of the flow on the long term, since the actual flow in the Palcoma River will be variable. By modelling the discharge on a monthly basis, the effect of the quick runoff on the total runoff is not important. However, since the capacity of the pipeline is limited, the variability of the available flow can make it difficult to use the intake to the full potential. This could pose a problem, especially regarding the future ambition of EPSAS to increase the intake percentage.

A final topic for discussion is whether the intake-volume relationships can directly be used to determine the control actions based only on the month within the wet season, the control strategy and the stored volume of water in the reservoirs. Such an approach would omit the effect of the initial hydrological conditions on the precipitation scenarios and thus on the available amount of water in the supply system. It would be interesting to study these effects on the operational control. Another drawback of this approach is the changing demand of the WTPs. When the demand changes the intake-volume plots become inaccurate, which would make a new simulation necessary. This situation also applies when the infrastructure of the water supply system changes.

6 Conclusion and recommendations

This chapter of the report will present the conclusions that answer the research questions and describe some recommendations to improve and expand this research.

6.1 Conclusion

To draw the conclusions of this study, the research questions introduced in chapter 1.5 will be answered. First, the research questions regarding the rainfall-runoff modelling are answered, consequently the research questions regarding the long-term simulation and decision support on real-time control are answered and finally the overall conclusion is drawn.

6.1.1 Rainfall-runoff modelling

What are the hydrological boundary conditions for the water supply system?

It can be concluded that three variation patterns in the rainfall greatly impact the hydrological boundary conditions of the water supply system; variation within the hydrological year, the interannual variation and the spatial variation between Incachaca and Hampaturi. Another important characteristic impacting the hydrological boundary conditions is the difference in the rainfall-runoff process between Incachaca and Hampaturi.

1. *What is the variability of the rainfall and runoff and how can this be modelled in an appropriate way?*

Given the task within this study to model the rainfall-runoff on a monthly scale, the variability of the quick runoff component is not very important. The dynamic interaction between the wet seasons and dry seasons on the other hand is very important. Especially the timing and shape of the peak discharge during the wet season has an impact on the operational control. It can also be concluded that the interannual variability in rainfall and runoff is important. One dry year may be compensated by the amount of stored water in the reservoirs, but multiple consecutive dry years can lead to water shortages. Furthermore, the spatial variation of rainfall can be large, potentially leading to great differences in runoff between Incachaca and Hampaturi, which makes the operational control of the water distribution between the WTPs more dynamic. Concerning the rainfall-runoff process, Hampaturi responds quicker to precipitation and a larger part of the precipitation is transformed into runoff compared to Incachaca. Consequently, shortages at WTP Pampahasi are resolved earlier than shortages at WTP Chuquaiguillo.

It can also be concluded that the initial hydrologic conditions can have a major impact on the runoff. This effect can impact the catchment runoff up to three or four months. Especially during the wet season, the possible deviations in discharge can be substantial, having a major impact on the available volume of water inside the water supply system. So, it proves to be a good choice to use a conceptual model for the rainfall-runoff modelling in this study.

2. *What are appropriate precipitation scenarios?*

The three variation patterns as described above; the variation within the hydrological year, the interannual variation and the spatial variation between Incachaca and Hampaturi greatly impact the hydrological boundary conditions of the water supply system and are therefore very important to include in the precipitation scenarios. An appropriate way to include these three characteristics into the precipitation scenarios is to establish scenarios based on historical records. By using two consecutive historical years for each scenario, the interannual variability is also included. Furthermore, in this way the variation in precipitation between Incachaca and Hampaturi is correctly introduced.

6.1.2 Long-term simulation and decision support on real-time control

What are the advantages of the real-time decision support?

The implemented decision support method proved to be clear and consistent according to the resulting Pareto front generated by the different trade-offs. The control strategies make it possible to clearly represent the different possible trade-offs between the water shortages and the operational costs. Subsequently, the real-time control actions are determined corresponding to the chosen control strategy.

3. *What is a consistent method for choosing the real-time control actions?*

The control strategies are a consistent and helpful method for the decision-maker to choose a trade-off that matches with the available financial resources and acceptable risk for having water shortages.

4. *How do the control strategies respond to different reservoir volumes?*

The control strategies are sensitive to the amount of water stored inside the reservoirs. In contrast to risky control strategies, conservative control strategies respond more intense by implementing higher intake discharges. Besides, a more conservative strategy starts to respond already to higher reservoir volumes in comparison to risky strategies. The riskiest control strategies respond very little to low reservoir volumes, because they are based on optimistic precipitation scenarios, which assume that a large amount of future precipitation will compensate the low reservoir storage. Furthermore, the response of the control strategies clearly becomes more intense as the wet season progresses, since at the end of the wet season the reservoirs need to store enough water to last the entire dry season.

5. *How do the control strategies relate to the trade-off between water shortages and operational costs?*

As expected a Pareto front is generated by the different control strategies, which represents the different possible trade-offs between water shortages and the operational costs. The main pattern is that for the conservative control strategies the shortages occur mostly at WTP Pampahasi. However, this is mainly caused by the control on the Incachaca – Pampahasi channel. To minimize the overall losses, the use of the channel is minimized. Furthermore, Incachaca has a higher relative runoff compared to the demand of its corresponding WTP in comparison to Hampaturi, which often result in the demand of WTP Chuquiaguillo being satisfied, while WTP Pampahasi is not.

6. *How does the trade-off between water shortage and operational costs change in the future?*

In the future the chance of having water shortages and the added operational costs will both increase. In 2027 the added operational costs might amount to 0.02 €/m^3 when choosing a conservative control strategy, which is not considered as critical. However, the water shortages will increase very quickly. Already in 2022 there will be shortages at the WTPs when using the intakes to the full potential. It can be concluded that in 2027 this water supply system will not suffice in satisfying the increased demands of the WTPs on a regular basis. This indicates that in the future the infrastructure is running into its limits and will be inadequate in delivering a reliable supply.

6.1.3 Overall conclusion

The objective of this thesis is the following:

Provide long term decision support on real-time control for the water supply system of La Paz by establishing an appropriate optimization approach to adjust the operational control to possible future hydrological conditions.

It can be concluded that this decision support can be a helpful tool for the decision maker to implement a consistent control strategy, by establishing the desired trade-off between the risk of having water shortages in the future and the additional operational costs of lowering this risk. To use this decision support to the full potential the decision maker should consider to what extent water shortages are acceptable and with which corresponding return period. On the other hand, it is important to consider what additional costs are acceptable for the consumers. In the future the chance of having water shortages will increase more quickly compared to the additional operational costs. When the decision-maker has determined the preferred trade-off, the decision support will provide real-time advice on a strategic level of how much water to take in and how to distribute it according to the different catchments.

6.2 Recommendations

As described in the discussion the precipitation scenarios can have an impact on the performance of the supply system. Within the method it was decided to use scenarios based on a repetition of two consecutive years. It is recommended to study the impact of this decision on the amount of water shortages and operational costs during a long term simulation. This can be performed by applying a statistical analysis to generate new scenarios and instead of using the scenarios of two consecutive years, make unique combinations of individual years. Furthermore, it is important to study the existence and possible effects of autocorrelations in the precipitation data and seasonal forecasts on the forecast uncertainty and if these can help to optimize the control actions.

Another recommendation is to investigate the impact of modelling the individual reservoirs within a catchment as one virtual reservoir, on the water supply. When this impact appears to be large the rainfall-runoff process of the different reservoir should be modelled individually. In that case additional precipitation data is required for every reservoir and therefore it is recommended to establish new measurement stations. Furthermore, the water levels and outflow of all the individual reservoirs should be measured.

Within the optimization process reservoir evaporation can be added as an additional optimization objective inside the sequential goal programming. In this way evaporation losses can be minimized, decreasing the water shortages. However, additional data is required to achieve this and therefore it is recommended to measure the daily evapotranspiration at every individual reservoir.

It is recommended to EPSAS to reconsider the social constraint at intake Palcoma. Now it is only allowed to use 35% of the discharge of Palcoma, while results demonstrate changing the constraint to 50% can already lead to a significant reduction in water shortages. Remarkably it can also lead to a reduction in additional operational costs.

It is also recommended to EPSAS to investigate the hydrological processes of Huayllara and Palcoma in more detail by making HBV-models based on local precipitation and discharge data. To make this possible extra precipitation and discharge gauges are recommended. Additionally, it is very important to study the hourly variability of the flow at Palcoma and Huayllara to determine if this variability limits the potential intake or not.

Another recommendation to EPSAS is to study the possibility of adding a reservoir to catchment Palcoma to generate storage capacity. This will make the use of the Palcoma intake less complex and probably less expensive, since most of the sediment will deposit inside the reservoir. Furthermore, the results of this research prove that the current infrastructure will be inadequate in supplying the WTPs in the future.

It is recommended to Royal HaskoningDHV to investigate how an early warning system can be implemented in this real-time decision support tool. This will be helpful in situations when major water shortages are probable and cannot be prevented by taking in extra water. Subsequently, these water shortages can be mitigated by slowly reducing the supply to the WTPs in advance. It is also recommended to Royal HaskoningDHV to study the possibility of directly using the intake-volume relationships to determine the control actions, since this might be an easier method to determine the operational control.

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A1 Precipitation and temperature correction

To perform the precipitation and temperature correction, first lapse rates are calculated according to the local precipitation and temperature data. Then, the average basin altitudes of Incachaca, Hampaturi and Palcoma are calculated. Multiplying the lapse rates with the elevation differences results in a correction factor for each individual basin.

Precipitation lapse rate

Within the study area precipitation is only measured at the Incachaca and Hampaturi Bajo reservoirs, while these reservoirs are located at the lowest point of their respective drainage basins. The measurement station at Achachicala has a comparable altitude as Incachaca and Hampaturi and is located within the Choqueyapu basin (adjacent to the basin of Incachaca). Other precipitation measurements are available for El Alto and for La Paz, see Table 20.

Table 20: The precipitation datasets available for elevation analysis

Available precipitation datasets			
Location	Altitude	Period	Resolution
Achachicala	4383 m+MSL	1991 - 2016	Month
Incachaca	4369 m+MSL	2000 - 2016	Month
Hamapturi	4203 m+MSL	2000 - 2016	Month
El Alto	4071 m+MSL	1943 - 2016	Month
La Paz	3592 m+MSL	1976 - 2005	Month

In order to express the local relationship between elevation and precipitation, the stations Alto Achachicala, Incachaca and Hampaturi will be compared to El Alto and La Paz. First, the correlation is calculated for the overlapping time periods using Eq. (9):

$$\rho_{XY} = E[(X_n - \mu_X)(Y_n - \mu_Y)]/(\sigma_X \sigma_Y) \tag{9}$$

Then the relative volume difference (RVE) is calculated by summation of the difference between the 'low' station and the 'high' station for every time step (where both stations have measurements) and subsequently dividing this summation by the total precipitation of the 'low' station, see Eq. (10):

$$RVE = \frac{\sum_{t=1}^{T}(P_{high}^{t} - P_{low}^{t})}{\sum_{t=1}^{T}(P_{low}^{t})} \tag{10}$$

Dividing the RVE by the elevation difference results a precipitation lapse rate, which expresses the precipitation change per meter.

Temperature lapse rate

The air temperature is measured at the stations of El Alto and Achachicala. The method for determining the temperature lapse rate is analogous to the method used for the precipitation lapse rate.

Average basin altitude

A digital elevation model (DEM) is used to estimate the average altitude of the Incachaca, Hampaturi, Palcoma, Hampaturi Bajo and Ajuan Khota basins. Since Palcoma has no precipitation station, it is assumed that the data from Hamapturi is representative for the basin of Palcoma. Palcoma is adjacent to Hampaturi and has comparable elevation characteristics. Multiplying the elevation differences with the precipitation and temperature lapse rates, result in correction factors which can be applied to correct the precipitation and temperature measurements to become representative for their entire drainage basin.

Precipitation correction

Table 21 shows the correlation, RVE, elevation difference and lapse rate for different combinations of 'Low' and 'High' stations.

Table 21: Relation between 'low' and 'high' precipitation stations

Relation between precipitation stations					
'Low' stations	'High' stations	Correlation	RVE (%)	Elevation difference (m)	Lapse rate (%/m)
El Alto	Achachicala	0.914	-6.20	312	-0.020
El Alto	Incachaca	0.898	-4.87	298	-0.016
El Alto	Hampaturi	0.909	-6.36	132	-0.048
La Paz	Achachicala	0.892	14.42	791	0.018
La Paz	Incachaca	0.911	15.61	777	0.020
La Paz	Hampaturi	0.919	13.64	611	0.022
La Paz	El Alto	0.966	16.48	479	0.034

First of all, it is remarkable to see that the precipitation at the measurement station of El Alto is higher in comparison to the stations of Achachicala, Incachaca and Hampaturi, while El Alto has a lower elevation. Comparing the higher stations to the station at La Paz results in a more expected outcome, since this shows agreement to the orographic effect. The orographic effect is commonly referred to as the positive effect of mountain slopes on the precipitation (Daly et al., 1993). The reversed orographic relationship between El Alto and the stations of Achachicala, Incachaca and Hampaturi may be explained by the effect of the altiplano. El Alto is located on this altiplano, which is a highland plateau at the central area of the Andes cordillera, running continuously in a north-south direction (Garreaud et al., 2003). Since the 'high' stations are located at the east side of the Andes cordillera, it might be possible that the local precipitation over the altiplano is blocked by the relief of the east side of the Andes cordillera. This could cause the precipitation systems to get 'trapped', resulting in more rainfall at El Alto than at La Paz, Achachicala, Incachaca and Hampaturi.

The stations of Achachicala, Incachaca and Hampaturi also show a better correlation with La Paz then with El Alto. We assume that the relationship between La Paz and the 'high' stations is representative for the orographic effect between the measurement stations of Incachaca and Hampaturi and their higher situated drainage basins. It is decided to use a precipitation lapse rate of 0.02%, which is the average of the lapse rates of 0.018 %, 0.020 % and 0.022 %, see Table 22 for the resulting precipitation correction. The average elevation of Hampaturi Bajo and Ajuan Khota are apparently identical.

Table 22: Average elevation, elevation difference and precipitation correction factor

Precipitation correction using a lapse rate of 0.02%			
Basin	Average elevation	Difference with measurement station	Precipitation correction factor
Incachaca	4805 m+MSL	436 m	1.087
Hampaturi	4901 m+MSL	698 m	1.140
Palcoma	4878 m+MSL	675 m	1.135
Hampaturi Bajo	4902 m+MSL	699 m	1.140
Ajuan Khota	4901 m+MSL	698 m	1.140

Temperature correction

The average temperature difference between the stations of Alto Achachicala and El Alto is 3.9 °C. Given the elevation difference of 312 meters between these stations, the temperature decreases with 1.25 °C per 100 meter elevation increase. See Table 23 for the corrections of the temperature data from Alto Achachicala and the temperature data from El Alto airport.

Table 23: Average elevation, elevation difference and temperature correction factor

Temperature correction using a lapse rate of 1.25 °C per 100 meter					
Basin	Average elevation	Difference with station Achachicala	Temperature correction	Difference with station El Alto airport	Temperature correction
Incachaca	4805 m+MSL	422 m	5.3 °C	747 m	9.3 °C
Hampaturi	4901 m+MSL	518 m	6.5 °C	843 m	10.5 °C
Palcoma	4878 m+MSL	495 m	6.2 °C	820 m	10.3 °C

Comparing the found temperature lapse rate to values presented within the literature shows that 1.25 °C per 100 meter is a high lapse rate. Ayala et al. (2011) performed a study in a mountainous area of the Chilean Andes between altitudes of 2100 – 4831 m+MSL and found an average lapse rate of 0.65 °C per 100 meter. A comparable study is performed by Córdova et al. (2016) at the southern Ecuadorian Andes between altitudes of 2600 – 4200 m+MSL and resulted in a mean lapse rate of 0.69 °C per 100 meter. Urrutia & Vuille (2009) investigated an overall lapse rate for the Andes and came up with a rate of 0.52 °C per 100 meter. However, they make a remark that rather abrupt changes in the temperature lapse rate are possible. For example, on the western side of the Andes there is an abrupt change occurring around 2500 m+mSL, with very low lapse rates at low elevations.

A2 Potential evapotranspiration

The potential evapotranspiration can be calculated using an equation from Penman as presented by Shaw (1994) (equation 11.20, page 270), see Eq. (11). In order to calculate the potential evapotranspiration as accurate as possible, it is important to include the daily variation of some of the input parameters. For this purpose, additional data is obtained with an hourly resolution over the period 2013 – 2016. This data is originating from the weather station located at the El Alto airport[1] and contains temperature, humidity and wind speed measurements. These temperature measurements are subsequently corrected for the altitude difference between El Alto Airport (4071 m+MSL) and the average elevation of Incachaca and Hampaturi (4870 m+MSL) according to the temperature lapse rate as presented in annex A1. The potential evapotranspiration resulting from the Penman equation is expressed per second, multiplying this by 60^2 * 24 results in the daily potential evapotranspiration.

$$E_t = \frac{\left(\frac{\Delta}{\gamma}\right) H + 0.35(1 + u_2/100\,) * (e_a - e_d)}{\left(\frac{\Delta}{\gamma}\right) + 1} \tag{11}$$

where: E_t is the evapotranspiration rate per second (mm m^{-2} s^{-1})
Δ is the gradient of the saturation vapour pressure curve at temperature T(∘C) (hPa K^{-1})
γ is the psychrometric constant (assumed to be constant at 0.0646 hPa K^{-1})
H is energy which is available for evapotranspiration (W m^{-2})
u_2 is the windspeed measured 2 meters above the surface level (m/s)
$e_a(T_a) - e_d$ is the vapour pressure deficit (hPa)

These parameters are described in the order as identified above. Some of the parameters are not yet known, these will be calculated or taken from other sources. Representative values can be found in Table A4 from Shaw et al. (2011) based on the air temperature (∘C). The hourly temperature data from the El Alto airport were used to find hourly values for Δ using linear interpolation. Subsequently, these hourly values were averaged to come to daily average values. H is calculated using equations (12), (13) and (14), originating from Shaw et al. (2011). The vapour pressure deficit is defined as: $e_a(T_a) - e_d$ and is calculated using the hourly saturated vapour pressure and hourly humidity values. Multiplying the humidity by the saturated vapour pressure results in the actual vapour pressure, subtracting this vapour pressure from the saturated vapour pressure results in the vapour pressure deficit.

$$H = R_I(1 - \alpha) - R_O \tag{12}$$

$$R_I(1 - \alpha) = (1 - \alpha)R_a \cdot f_a\left(\frac{n}{N}\right) \tag{13}$$

$$f_a\left(\frac{n}{N}\right) = 0.18 + 0.55\left(\frac{n}{N}\right) \tag{14}$$

where: R_I is the incoming radiation (W m^{-2})
R_O is the outgoing radiation (W m^{-2})
α is the albedo, the ratio of reflected short-wave radiation to incoming short-wave radiation
R_a is the clear sky radiation (W m^{-2})
f_a is a function of the ratio (n/N)
n is the number of bright sunshine hours per month
N is the number of daylight hours per month

[1] http://rp5.md/Weather_archive_in_La_Paz,_El_Alto_(airport),_METAR

Within the literature different albedo values can be found corresponding to grass or tundra. According to "Climate Data Information" (n.d.), grassland and tundra have an albedo of 0.25 and 0.2 respectively. While Coakley (2003), argues that grassland an tundra have albedos of respectively 0.21 and 0.17. According to "Center For Science Education" (n.d.) the values for albedo range between 0.25 – 0.3 and 0.15 – 0.35 for grass and tundra respectively. An albedo value of 0.25 is considered appropriate, since most of the study area consists of grassland.

Daily values for R_a can be calculated by the interpolation of values found in Table A1 from Shaw et al. (2011). Values of *n* representative for an average year for La Paz are found on the website from the "World Weather & Climate Information" (n.d.) and shown in Table 24. Values for N for the location of La Paz can be retrieved from the website of the "U.S. Naval Observatory" (2015) using latitude of -16 °30 and longitude -68°1, see Table 24. These values were interpolated linearly to become daily values.

Table 24: Average amount of daylight and sunshine hours per month for La Paz

Average monthly hours of daylight and sunshine												
	JAN	FEB	MRT	APR	MEI	JUN	JUL	AUG	SEP	OKT	NOV	DEC
N (hours)	400	354	378	354	351	336	349	360	360	386	387	406
n (hours)	190	145	155	170	250	270	280	250	210	185	180	185

R_O can be calculated using the following formula from Shaw et al. (2011), see Eq. (15):

$$R_O = \sigma T_a^4 (0.56 - 0.092 e_d^{0.5}) \left(0.1 + 0.9 \left(\frac{n}{N}\right)\right) \tag{15}$$

where: σ is the Stefan-Boltzman constant (5.6704·10^{-8} W m^{-2} K^{-4})
T_a is the mean air temperature in the required period (K)
e_d is the saturated vapour pressure (hPa) at temperature (K)

Values for the saturated vapour pressure can be found at Table A4 of Shaw et al. (2011). These values can be interpolated on an hourly basis according to the temperature data.

Since the hourly temperature, humidity and wind speed measurements are only available over the period 2013 – 2016 it is decided to calculate the daily PET for an average year. Different temperature lapse rates are included in the PET calculations to show the sensitivity of the PET to temperature. As can be seen in Table 25, the minimum PET values are not very sensitive to the temperature lapse rate. However, the max and mean values are more sensitive to the temperature lapse rate, also shown by the standard deviation. Comparing the calculated PET values to the ET estimates from the catchment water balance shows that the PET values are two to three times higher than the ET estimates.

Table 25: Min, max, mean and standard deviation of the calculated PET

Calculated PET						
	Lapse rate: 0.006 °C/m		Lapse rate: 0.01 °C/m		Lapse rate: 0.0125 °C/m	
	Daily	Monthly	Daily	Monthly	Daily	Monthly
Min	1.04 mm	32.8 mm	1.00 mm	32.0 mm	0.98 mm	31.7 mm
Max	3.18 mm	98.3 mm	2.98 mm	93.4 mm	2.85 mm	90.3 mm
Mean	2.33 mm	72.3 mm	2.17 mm	68.6 mm	2.08 mm	66.4 mm
St Dev	0.6269		0.5993		0.5791	

Comparing the found PET rates to PET and ET values presented within the literature shows that the rates presented in Table 25 are comparable to PET values found in the Andes region. According to Chanduvi-Acuña (1969), who performed a study about evapotranspiration in Peru, average daily measured PET values vary between 2.88 and 3.98 mm/day according to different measuring stations between altitudes of 1800 and 3820 m+MSL. They performed their measurements using an evaporation pan. Fiorella et al. (2015) investigated long-term average potential evapotranspiration in the Bolivian and North-Chile Andes and estimated that the PET varies roughly between 1 and 4 mm/day. Carrillo-Rojas et al. (2016) performed a study about the mapping of evapotranspiration using Landsat and MODIS imagery for the Andes in Southern Ecuador between altitudes of 3300 and 3950 m+MSL. They calculated the monthly evapotranspiration and validated the outcome with a catchment water balance. Their results vary between 40 - 50 mm for the months Jun – Sep and between 100 - 110 mm for the months Jan – May.

A3 Reservoir water balance

During the 2000 -2016 period, the basins of Incachaca and Hampaturi both consisted of four reservoirs. The outflow, spill and reservoir levels are only measured at the Incachaca, Hampaturi Bajo and Ajuan Khota reservoirs. The water level measurements are converted into water volumes by using water level/volume relationships provided by EPSAS. By using the water volumes of two consecutive time steps, outflow and spill, the reservoir balance can be calculated, resulting in the inflow discharge, see Eq. (16):

$$Q_{in}^t = S^t - S^{t-1} - Q_{out}^t - Q_{spill}^t \tag{16}$$

where: Q_{in}^t is the reservoir inflow
S^t is the reservoir storage
Q_{out}^t is the reservoir outflow
Q_{spill}^t is the reservoir spill

Eq. (9) does not include direct precipitation and evaporation into the reservoir. The calculation of the reservoir inflows is performed for Incachaca, Hampaturi Bajo and Ajuan Khota, the unmonitored reservoirs which are located upstream are not included in these calculations.

The resulting discharges are plotted together with the precipitation to give an indication of the relation between these two variables. The precipitation data are corrected according to the precipitation lapse rate of 0.02%. Also, a graph showing the total discharge of Hampaturi is added by summing the calculated discharges of Hampaturi Bajo and Ajuan Khota.

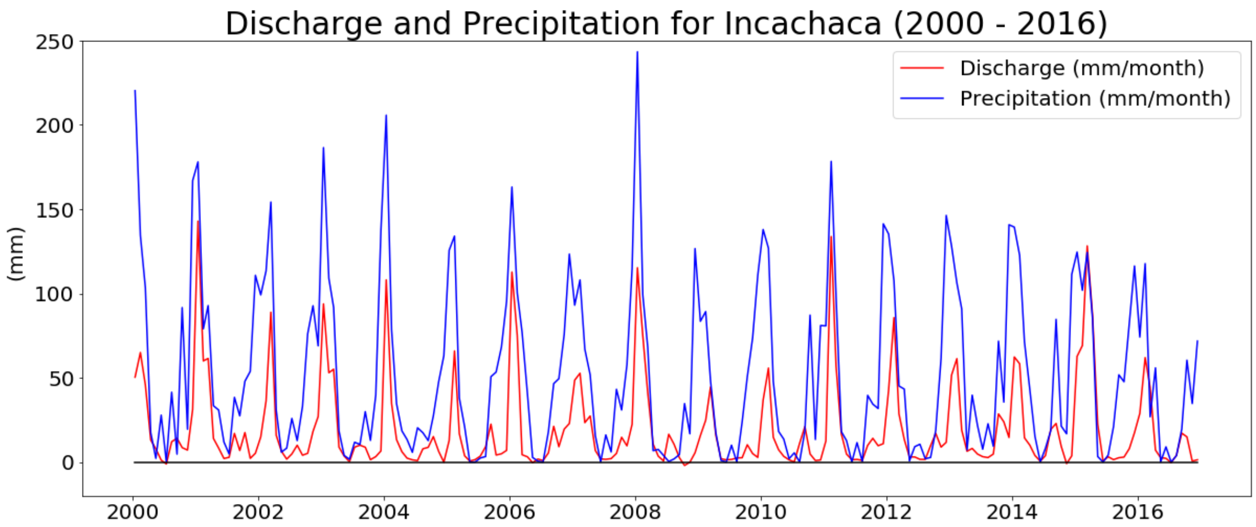

Figure 33: Discharge and corrected precipitation for Incachaca (2000 – 2016), precipitation is measured at reservoir Incachaca

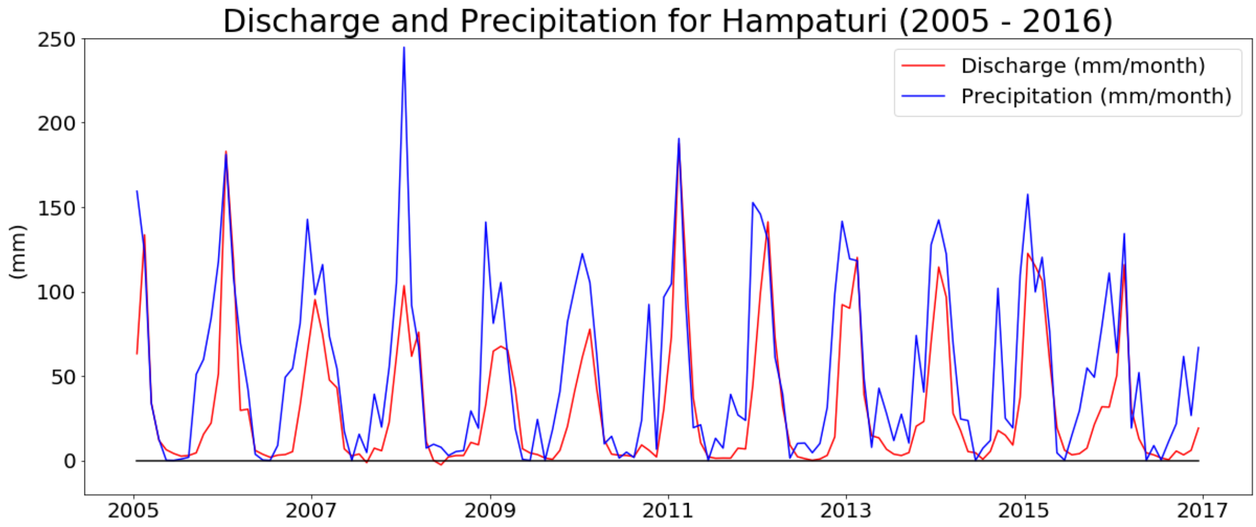

Figure 34: Discharge and corrected precipitation for Hampaturi (2005 – 2016), precipitation is measured at reservoir Hampaturi Bajo

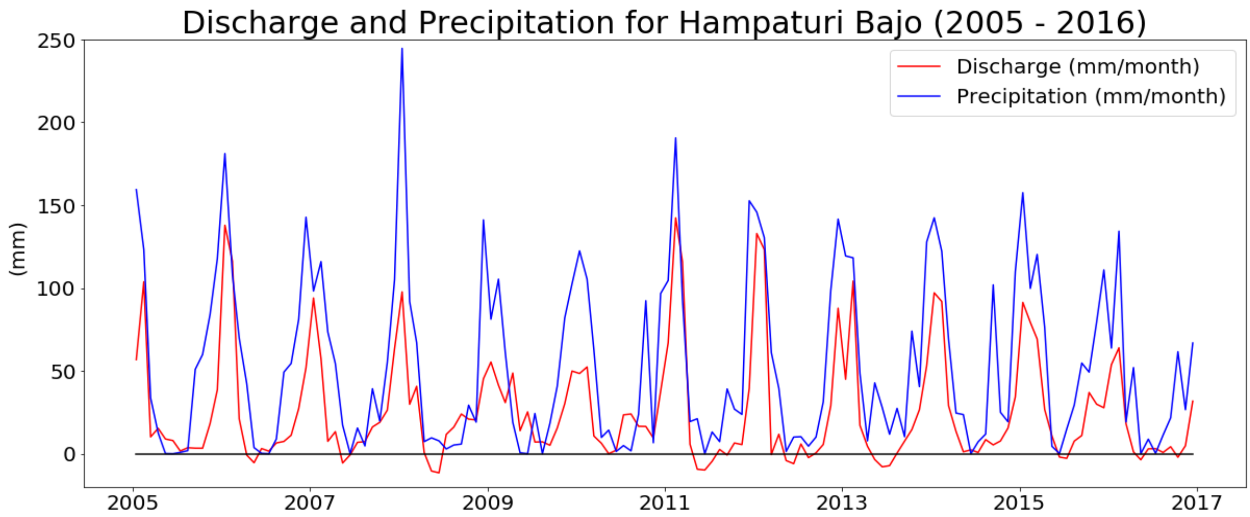

Figure 35: Discharge and corrected precipitation for Hampaturi Bajo (2005 – 2016)

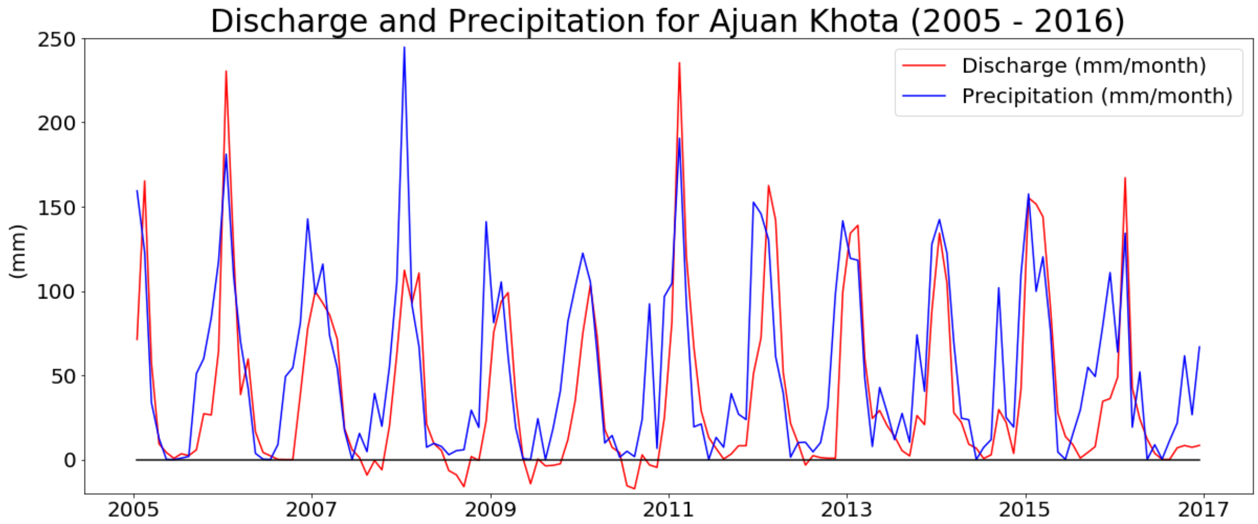

Figure 36: Discharge and corrected precipitation for Ajuan Khota (2005 – 2016), precipitation is measured at reservoir Hampaturi Bajo

It is striking to see that in Figure 33 the discharge into reservoir Incachaca does not match the precipitation during most dry periods. This can be explained by the effect of upstream reservoirs that are unmonitored and are therefore also not included in the reservoir balance. See Table 26 for the monitored and unmonitored reservoirs.

Table 26: Storage capacity of the monitored and unmonitored reservoirs inside the Incachaca and Hampaturi basins

Incachaca			
Monitored reservoirs	Capacity (Mm3)	Unmonitored reservoirs	Capacity (Mm3)
Incachaca	5.16	Quinquillosa	0.50
Total	**5.16**	Estrellani	0.84
		Sorajahuira	0.26
Rel (%)	**24**	**Total**	**1.60**

Hampaturi			
Monitored reservoirs	Capacity (Mm3)	Unmonitored reservoirs	Capacity (Mm3)
Hampaturi Bajo	3.02	Serkhe Khota	0.35
Ajuan Khota	3.46	Kunkahuikara	0.38
Total	**6.48**	**Total**	**0.73**
Rel (%)	**10**		

Important in Table 26 is the relative difference between the storage capacity of the monitored and unmonitored reservoirs. For the Incachaca basin the unmonitored storage is 24% in comparison to the total storage, while for the Hampaturi basin this only amounts to 10%. This has great impact on the accuracy of the calculated streamflow discharges, since the upstream reservoirs are used to store extra water within the basin but are only supplying water to the larger reservoirs when their water levels have declined significantly. Usually these upstream reservoirs are emptied in a short amount of time during the dry period. According to EPSAS (2014) these operations usually begin in August and lasts one or two months. The data itself suggests that these operations are mostly performed in August and September, but often also in October. Because the unmonitored reservoirs are emptied in the dry period and drain into the monitored reservoir(s), the calculated stream flows show errors, see Figure 33 and Figure 34. The stored volume of the unmonitored reservoirs drains during the dry season, while most of their stream flows would naturally occur during the prior wet season. Clearly, this effect is more present at Incachaca than at Hampaturi.

Another anomaly in the data becomes visible when the discharge of the entire Hampaturi basin is not aggregated, but split for two reservoirs; Hampaturi Bajo and Ajuan Khota, see Figure 35 and Figure 36. The calculated discharges resulting from these reservoir balances show large negative values. For

Hampaturi Bajo these negative values range up to 320,000 m^3 for a single month and 650,000 m^3 for a single year. For Ajuan Khota these negative values range up to 490,000 m^3 and 1,200,000 m^3 respectively. These anomalies are too large to be explained by direct reservoir evaporation, since a loss of 15% of the reservoir volume in one month is unrealistic. There is no direct water use from the reservoirs, so water can only leave the reservoirs by outflow or spill. As Table 26 shows, the upstream reservoirs Serkhe Khota and Kunkahuikara only have storage capacities of 350,000 m^3 and 380,000 m^3 respectively, so these anomalies can also not be explained by the effects of upstream reservoirs.

At Hampaturi Bajo the negative discharges occur mostly in the months May, June and July, while at Ajuan Khota they mostly occur in the months August, September and October. Also, the years in which these anomalies occur differ greatly between the two reservoirs, the only years showing an overlap are 2007 and 2008, see Figure 35 and Figure 36. When aggregating the two reservoir balances into one balance, these negative values are mostly compensated by larger positive values, resulting in a discharge for Hampaturi with only two minor negative values (in 2007 and 2008), see Figure 34.

Remaining causes for these negative anomalies in the discharges are errors in the water level measurements, errors in the water level/volume relationships and/or errors in the outflow measurements. Errors in the spill measurements are not a possible cause, since spill does not take place in the dry season. Since the water levels of the reservoirs are recorded manually every day by using a measuring tape, it is not likely that there are large errors on a monthly time scale. The largest uncertainties are probably present within the water level/volume relationships and outflow measurements. It is unclear how the water level/volume relationships are established, furthermore the method used to determine the outflow discharges is ambiguous. This method is based on water level measurements of the flow arriving at WTP Pampahasi, which is transformed in discharge using a Q-h relationship. However, since the Incachaca and Hampaturi basins are both connected to Pampahasi, it is unclear how EPSAS has determined which part of the discharge is originating from Incachaca and which part from Hampaturi.

Adjusting inflow discharge of Incachaca

As shown in Figure 33, the effects of upstream unmonitored reservoirs are clearly visible in the reservoir inflow discharge of Incachaca. Since this discharge timeseries will be used to calibrate and validate the HBV model, it will be adjusted for this effect. The adjustments are performed in such a way that the total volume over the period 2000 – 2016 remains the same.

First, the water volumes coming from the upstream reservoirs are isolated for each year individually. Generally, these discharge peaks are well recognizable, as they occur in August, September and October. To decide whether discharge belongs to upstream reservoirs or not, it is good to realize that this discharge is annually constrained by the total upstream storage volume, which is equal to 1.6 Mm^3. Since the reservoirs are filled and released maximum once a year, the discharge belonging to these upstream reservoirs cannot exceed 1.6 Mm^3. Comparing the discharge to the corresponding precipitation can be an indicator whether a discharge peak is caused by an upstream reservoir or is due to a precipitation event. Low or zero precipitation during the dry period indicates that a discharge peak is due to upstream reservoirs. When the difference between such a discharge peak and the precipitation is small, this assumption cannot be made.

Secondly, the isolated water volumes are distributed over the wet period preceding the dry period they are originating from. This is probably the best approach since the stored water that is released during the dry period, would have been discharged during the previous wet period without the upstream reservoirs. The isolated volume is distributed over the preceding wet period according to its relative discharge. The peak discharge of the wet period receives more of the isolated volume than the lower discharges. In this way, the isolated volumes are distributed along the wet periods in a ‘natural’ manner. Figure 37 shows the adjusted discharge of Incachaca. The isolated water volumes are presented in Table 27.

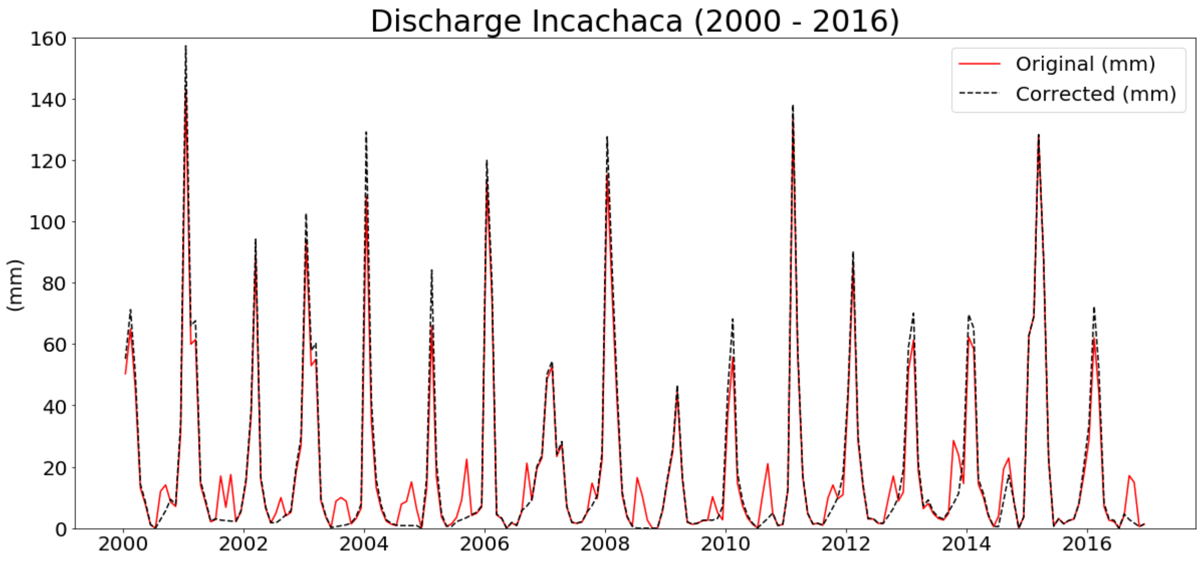

Figure 37: Observed discharge of Incachaca adjusted to overcome the effects of upstream reservoirs

Table 27: Isolated water volumes belonging to the upstream reservoirs of Incachaca

Isolated water volumes (Mm3)								
2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
0.61	1.17	0.35	0.87	1.20	0.96	0.48	0.25	1.02
2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	
0.35	0.94	0.46	0.56	1.15	0.67	0	0.95	

A4 Catchment water balance

To have an indication of the average evapotranspiration in the different basins, catchment-scale evapotranspiration estimates can be obtained by using the water balance equation from Shaw et al. (2011), see Eq. (17):

$$E_t = P - Q - G \pm \Delta S \tag{17}$$

where: E_t is the catchment average actual evapotranspiration
P is the estimated catchment average precipitation
Q is the measured stream discharge
G is groundwater discharge across the basin divides
ΔS is the change in storage

The precipitation and streamflow discharges have a monthly resolution and are known for Incachaca over the period 2000 – 2016 and for Hampaturi Bajo and Ajuan Khota over the period 2005 – 2016. The precipitation was corrected using a lapse rate of 0.02%. There is no data available about groundwater flow, so the groundwater discharge is not explicitly included in the water balance. Probably a major part of the groundwater flow will contribute to the basin discharge occurring on the surface. The netto groundwater discharge across the boundaries of the basin is assumed to be zero.

The storage applies to all the water that is stored within the catchment; the top soil layer, deeper in the ground, in glaciers and in reservoirs. Only the reservoir storage is explicitly included in the catchment water balance. The other storages are not included, since it is assumed that these storages are constant over time. To minimize the impact of this assumption, the catchment water balance is assessed using hydrological years. The hydrological year is defined as follows: it starts in July and ends in June. The results of the catchment water balance are presented in Table 28. Also, results are included based on other precipitation lapse rates to indicate the sensitivity of the catchment water balance to the precipitation. The evapotranspiration values are pretty sensitive to the precipitation lapse rates, so they can only be used as rough indications.

The average evapotranspiration is 33 mm per month for Incachaca and 21 mm per month for Hampaturi. However, the variation during the year is large, with the wet season having a higher difference between precipitation and discharge than the dry season. Also, at the beginning of the wet period this difference is larger than in the middle or at the end of the wet period. This effect is probably caused by the soil storage, because during the dry period the soil storage is gradually emptying resulting in a 'dry' soil, whereas at the beginning of the wet period most of the precipitation is recharging the soil storage instead of discharging quickly. Because of this effect, the actual evapotranspiration is probably highest at the end of the wet period, since the soil storage is most saturated at that moment and the potential evapotranspiration is highest during the wet season.

Table 28: Evapotranspiration estimates according to the catchment water balance for different basins

Evapotranspiration estimates			
Hydrological year (Jul – Jun)			
	Lapse rate: 0.02	**Lapse rate: 0.034**	**Lapse rate: 0.1**
Incachaca	32.9 mm/month	36.0 mm/month	51.0 mm/month
Hampaturi	21.4 mm/month	26.1 mm/month	47.9 mm/month
Hampaturi Bajo	27.9 mm/month	32.7 mm/month	54.5 mm/month
Ajuan Khota	14.4 mm/month	19.1 mm/month	40.9 mm/month

It is remarkable to see that there is a major difference between the basins of Incachaca and Hampaturi. Furthermore, there is a difference between the sub-basins Hampaturi Bajo and Ajuan Khota. Figure 36 shows that during some of the wet seasons, the discharge at Ajuan Khota is larger than the precipitation at Hampaturi Bajo. Figure 35 shows that the discharge at Hampaturi Bajo is never larger than the precipitation. Since Hampaturi Bajo and Ajuan Khota have identical average elevations, it is remarkable to see that Ajuan Khota has a much higher discharge relative to the drainage area. This comparison suggests that the precipitation measured at Hampaturi Bajo is not representative for Ajuan Khota and that the latter is in reality receiving a lot more precipitation.

This spatial uncertainty in precipitation is probably also (partly) responsible for the difference between Incachaca and Hampaturi. Other effects contributing to this discrepancy are probably their differences in altitude, glacial storage, vegetation cover and relative storage capacity. As explained in the section 'Elevation correction', the average elevation of Incachaca is 4805 m+MSL, while Hampaturi has an average elevation of 4901 m+MSL. Usually evapotranspiration rates decrease with increasing elevation.

According to (EPSAS, 2014a) the Incachaca basin has no glacial coverage, while the Hampaturi basin has a coverage of approximately 1%, which contributes about 1.6% to the total discharge of the basin. It is estimated that this discharge contribution will decrease with 0.7% over the period 2011- 2040 (Nomden et al., 2017), so that the resulting glacial contribution will become 0.9% of the discharge in 2040. The glacial coverage is mainly provided by the Serkhe Khota glacier, which delivers its water to the Serkhe Khota reservoir. Since the glacier is shrinking, it is temporarily increasing the discharge of the Hampaturi basin. Because the glacial storage was excluded in the catchment water balance, this extra discharge is decreasing the basins difference between precipitation and discharge, leading to a smaller calculated evapotranspiration. However, this effect is very small since the glacial contribution to the basins discharge is minor.

Concerning the vegetation, Incachaca contains a bofedal with an approximate area of 0.5 km^2, which is modest in comparison to the total basin area of 34 km^2. Bofedals are a type of wetland naturally occurring at high altitudes and act like a sponge, by storing rainfall and glacial melt and releasing it steadily during dryer periods. It can have a major impact on the local soil storage. Bofedals function somewhat comparable to a manmade reservoir and also have an amplifying impact on the evapotranspiration. The Hampaturi basin does not possess such types of vegetation. It is unknown what the status of the bofedal at Incachaca is and if it is under threat in the future or has been in the past. The main threats to bofedals are overgrazing of livestock, the cutting of peat for use as fuel and mining activities (Fonkén, 2014). At least there are no mining activities taking place inside the Incachaca basin.

Another factor impacting the catchment water balance are the reservoirs. There is more storage capacity at Incachaca relative to the surface area of the basin in comparison to Hampaturi, see Table 29. This suggests that the direct evaporation from the reservoirs will be relatively higher for Incachaca than for Hampaturi.

Table 29: Reservoir storage capacity relative to the drainage basin surface area

Reservoir storage relative to surface area			
	Storage capacity	Surface area	Relative
	Mm3	km2	Mm3/km2
Incachaca	6.8	34.6	0.20
Hampaturi	7.2	59.4	0.12

A5 Control script

The control script calculates the control actions on the Palcoma and Huayllara intakes, the Incachaca – Pampahasi pipeline and consequently the water balance of the entire water supply system. See Figure 38 for the structure of the control script.

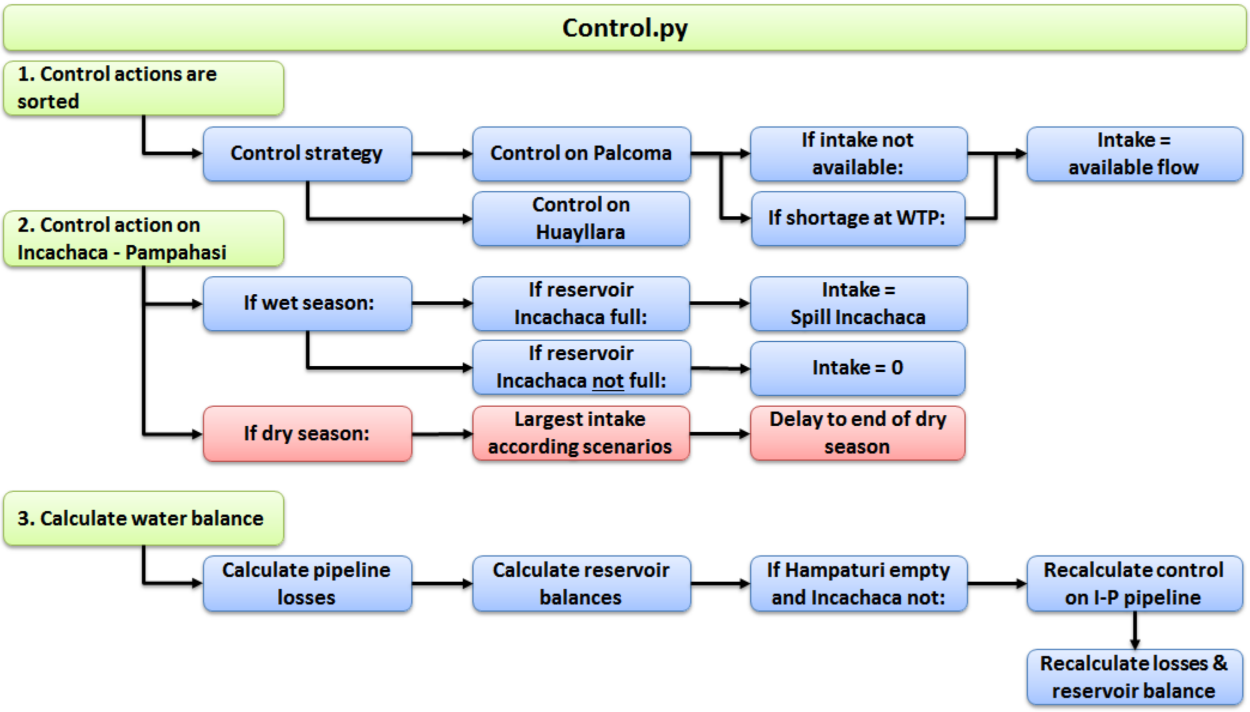

Figure 38: Flow chart presenting the structure of the control script

The first step of the control script is to determine the control actions on the intakes of Huayllara and Palcoma. The set of control actions from RTC-Tools is sorted from large to small based on their intake discharge. Consequently, the control actions are determined based on the prespecified control strategy and this sorted set of control actions.

Since the flow at Palcoma is determined using the HBV-model, it is variable over time, in contrast to the Huayllara intake where an assumption is made about a fixed possible intake. Because the flow at Palcoma is variable, the flow between the scenarios and the base case is also variable. As a result, it is possible that the proposed intake is higher than the available flow at Palcoma according to the base case. It is also possible that the chosen control action is constraint by the flow in its corresponding scenario, potentially leading to a water shortage, while the available flow at Palcoma might be higher in the base case. To prevent these situations from happening it is checked if the flow according the control action is available, and second if the proposed control action does not result in a shortage at WTP Pampahasi. If one of these checks is true, the control action on intake Palcoma is set equal to the available flow in the base case.

The second step of the control script is to determine the control action on the Incachaca – Pampahasi channel. This control is especially important during the dry season, when an improper distribution of water between the Incachaca and Hampaturi reservoirs can lead to unnecessary water shortages at one of the WTPs. By following the scenario involving the largest use of the Incachaca – Pampahasi channel, it can be determined what the maximum total intake on the channel should be until the end of the dry period (according to that scenario). By recalculating the control actions in such a way that the intake is delayed to the end of the dry season as much as possible, unnecessary use of the channel can be prevented. This also minimizes the losses, since this channel has a loss of 10%. During the wet season the channel is not used, except to prevent reservoir Incachaca for having spill.

The third step of the control script is to calculate the pipeline- and channel losses and consequently the water balance of the reservoirs. In contrast to the implementation in RTC-Tools, the losses according to Table 12 are implemented correctly in the control script. These new reservoir balances are calculated according to the pipeline losses, demands of the WTPs and the reservoir inflows from HBV.

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A6 Splitting HBV-model of Hampaturi in Hampaturi Bajo and Ajuan Khota

When the Hampaturi basin is split into two separate models for Hampaturi Bajo and Ajuan Khota, the model performance decreases. For Ajuan Khota the model performance is clearly influenced by a bias in the precipitation data. Increasing the precipitation lapse rate results in a better model performance regarding NS, see Table 30. The negative values present within the observed discharge are set to zero, since it is physically impossible to have negative discharge values.

Table 30: Calibrated HBV-model of the Ajuan Khota basin

Calibrated model parameters					Lapse rate: 0.02		Lapse rate: 0.05	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS	RVE [%]	NS
1	40	2	25	0.08	0.37	0.5795	34.49	0.6738

The simulated discharge using the lapse rate of 0.02 is plotted in Figure 39.

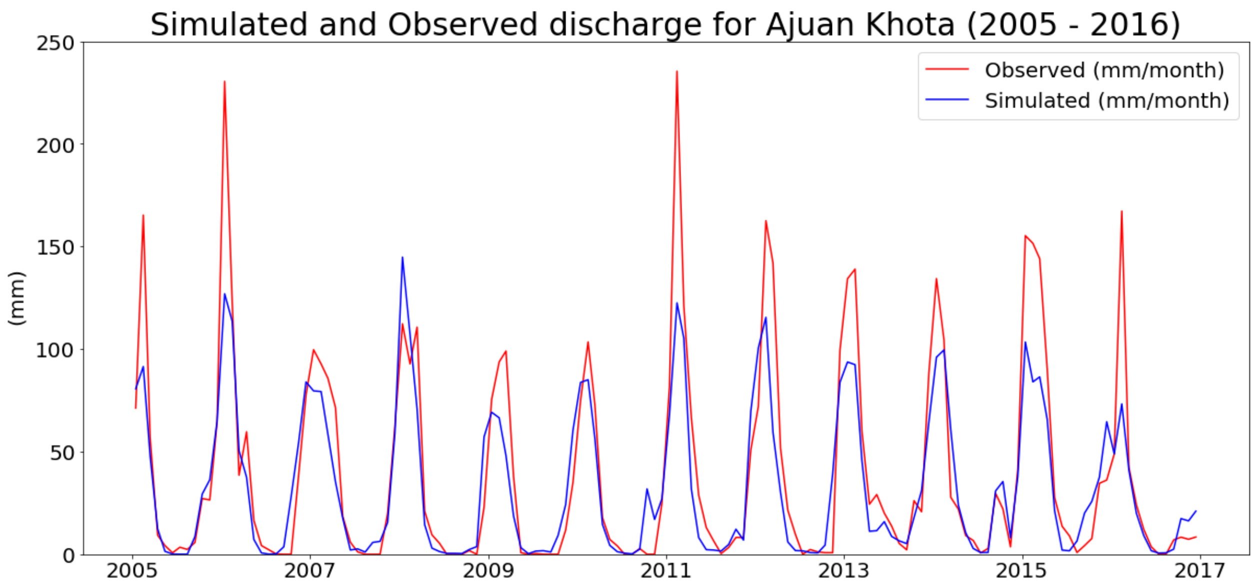

Figure 39: Hydrograph for the Ajuan Khota basin showing simulated and observed discharges

The calibrated model parameters of Hampaturi Bajo and corresponding values of RVE and NS are shown in Table 31. The simulated discharge is plotted in Figure 40.

Table 31: Calibrated HBV-model of the Hampaturi Bajo basin

Calibrated model parameters					Calibration	
LP [%]	FC [mm]	Beta []	Perc [mm day^{-1}]	K4 [day-^{1}]	RVE [%]	NS
0.5	160	1	26	0.25	-3.17	0.6935

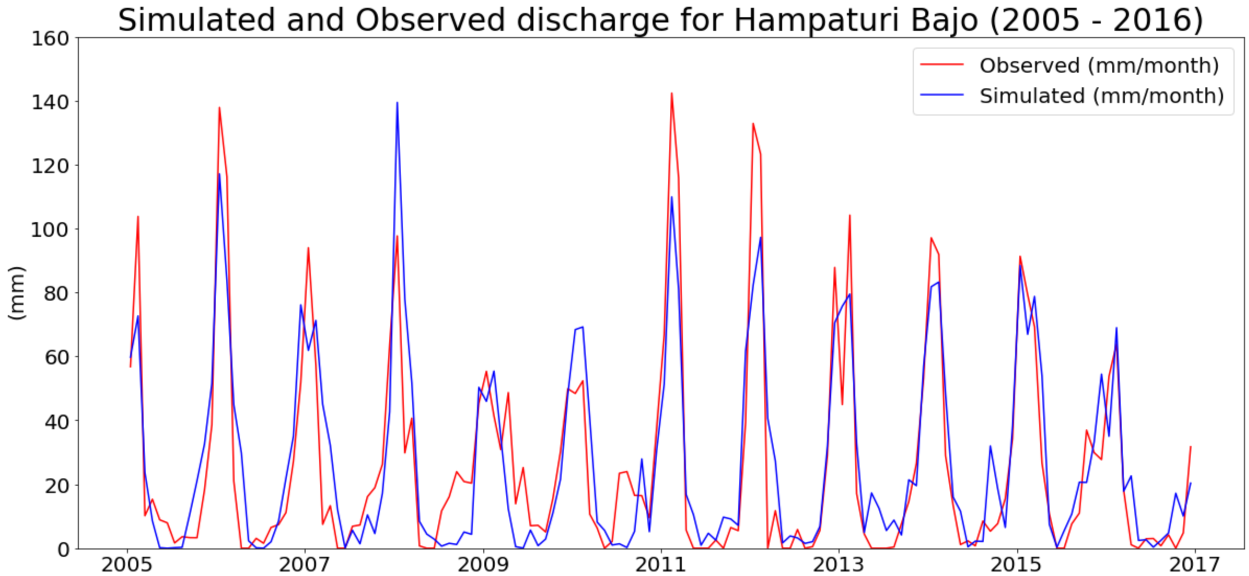

Figure 40: Hydrograph for the Hampaturi Bajo basin showing simulated and observed discharges

A7 Impact of initial hydrological conditions on the runoff

This annex presents the impact of varying initial HBV conditions on the runoff produced by the HBV-models. The results are presented in Figure 41 and Figure 42. To understand the behavior in different situations, the effects on a wet and a dry year are plotted during the wet season and the dry season. First the different initial hydrological conditions are established by running the HBV-models for the total 2000 – 2016 precipitation dataset and consequently for every initial condition the HBV-model is run for a wet year and a dry year.

Runoff during the wet season

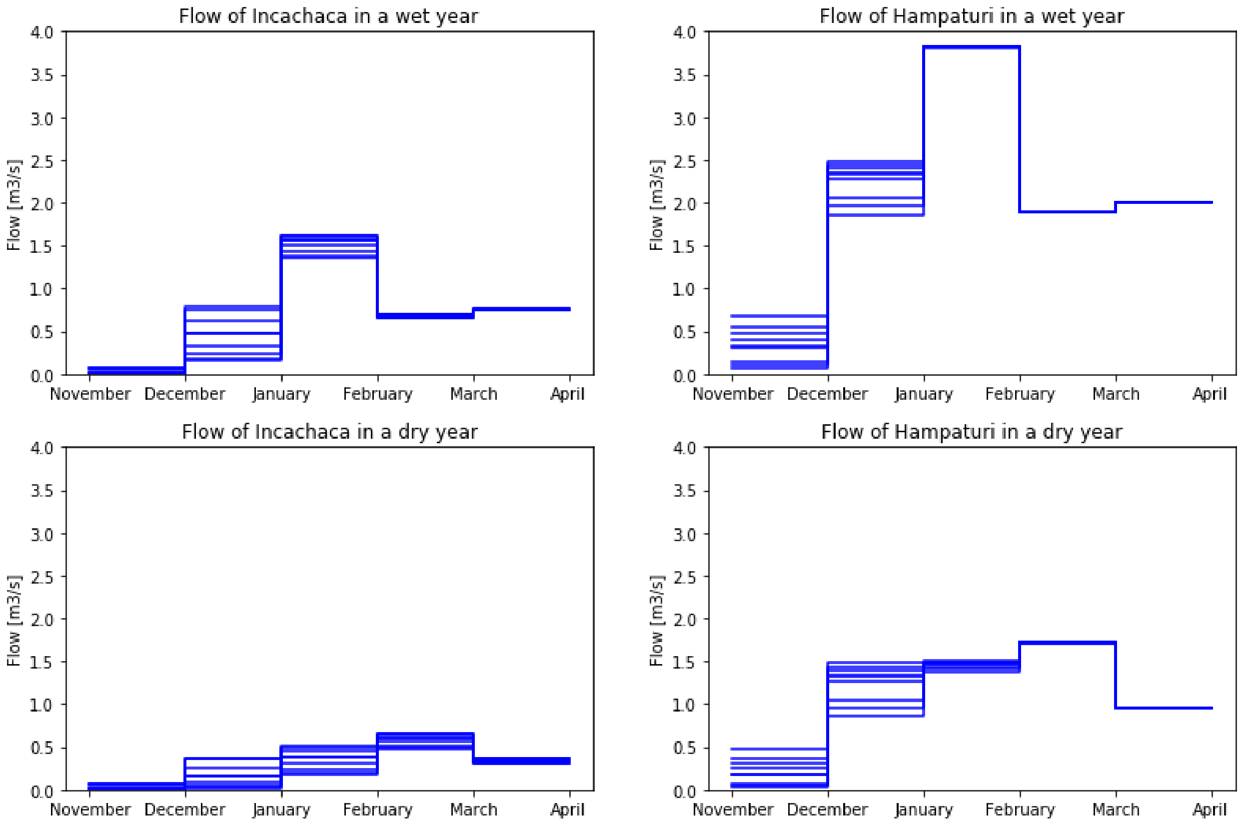

Figure 41: Effect of varying initial hydrological conditions on the runoff during the wet season for Incachaca and Hampaturi

During the wet season the runoff from Incachaca is affected for about three months in a wet year and up to four months during a dry year. The runoff from Hampaturi is affected for two months during a wet year and three months during a dry year. So, the impact on the Incachaca runoff is longer noticeable in comparison to Hampaturi.

During the dry season there are no noticeable differences between Incachaca and Hampaturi. It is remarkable to see that the effects of the varying initial conditions are opposite during the dry season compared to the wet season. Now the runoff in a wet year is influenced more by the initial conditions than in a dry year. However, during the dry season the relative effects of the varying initial conditions are large, but the absolute effects are rather small in comparison to the wet season.

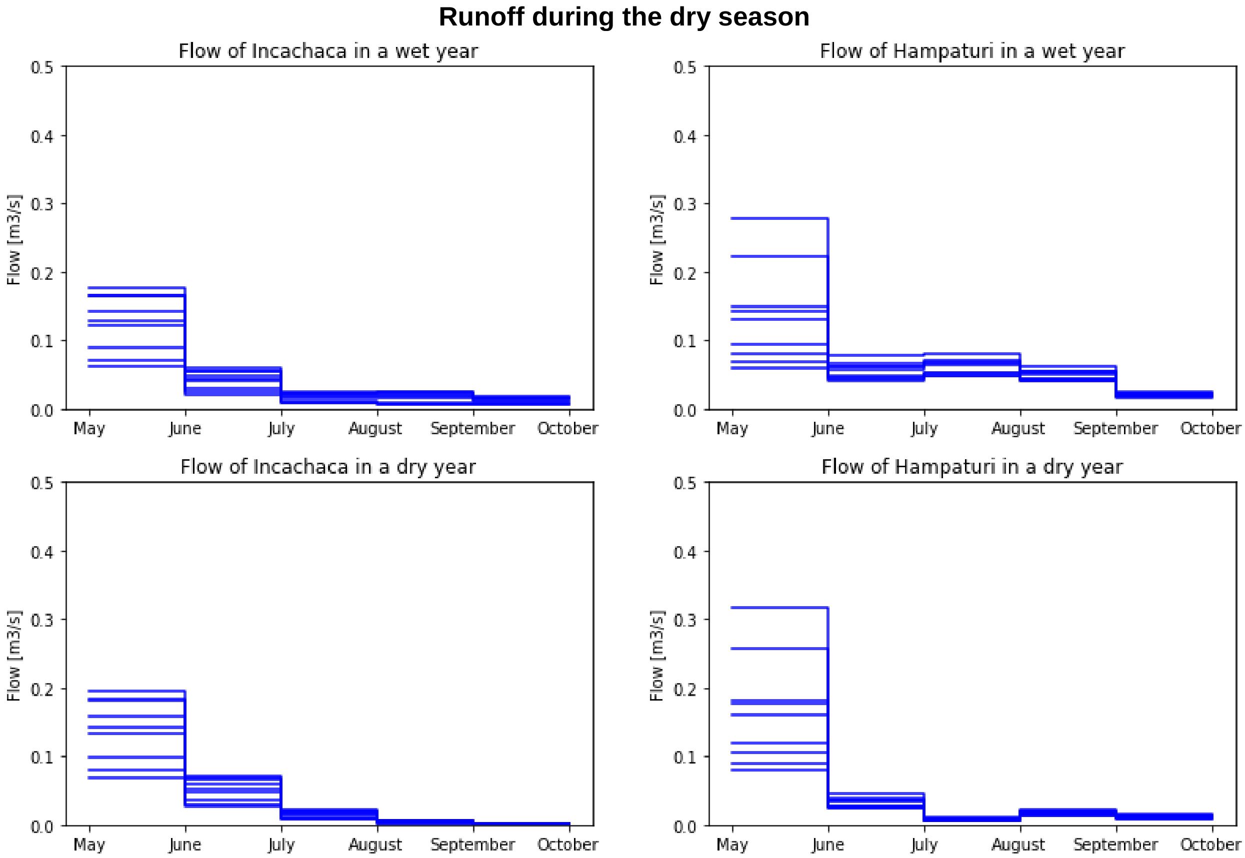

Figure 42: Effect of varying initial hydrological conditions on the runoff during the dry season for Incachaca and Hampaturi

A8 Long-term runoff simulation based on El Alto precipitation data

To place the 2000 – 2016 discharge data of Incachaca and Hampaturi in a broader perspective, additional discharges are simulated for the period 1943 – 1999 based on precipitation data from the El Alto station. First the precipitation is corrected based on the mean and standard deviation of the Incachaca and Hampaturi precipitation datasets respectively. Then, these corrected precipitation series are used as input for the HBV-models to generate runoff. See Figure 43, Figure 44 and Figure 45 for the results. An additional remark should me made regarding Figure 43, the discharge over the period 2000 – 2016 is generated based on the original precipitation data of Incachaca and Hampaturi, instead of the corrected El Alto data. That is also the reason for the variation between the discharge of Incachaca and Hampaturi which lacks during the 1943 – 1999 period. In Figure 43 the dry years of 2009 and 2010 which cause major water shortages in the long-term simulation are highlighted. Comparing these years to the simulated runoff from the El Alto data shows that this combination of two dry years is not unique. Figure 45 shows that the years 1956, 1957 and 1958 are all dry and especially Incachaca generates little runoff. Furthermore, also much drier years appear to occur according to the year 1983 shown in Figure 44.

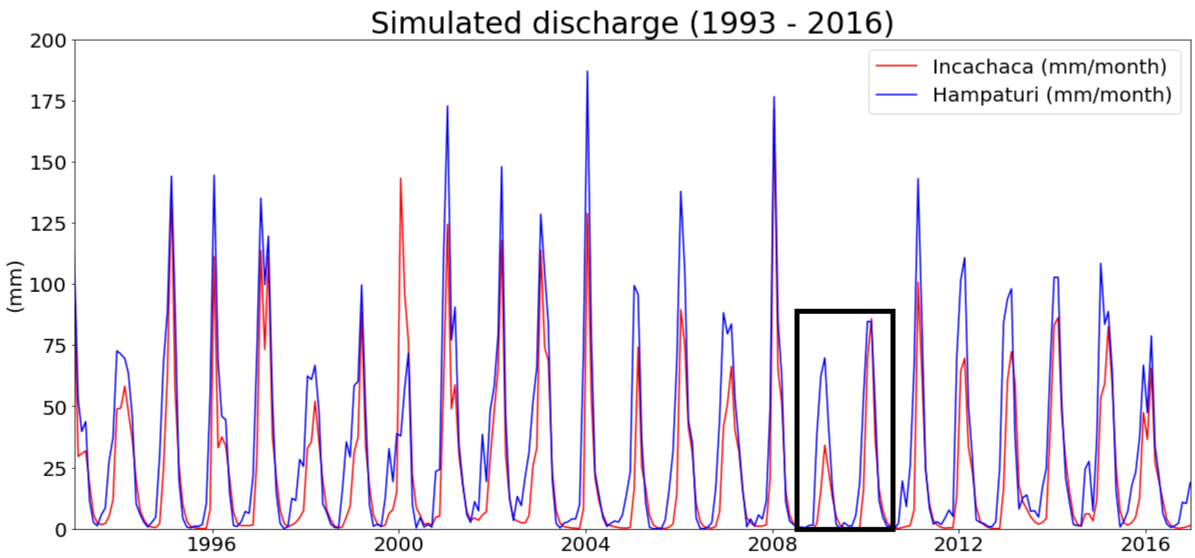

Figure 43: Simulated discharge of Incachaca and Hampaturi over the period 1993 - 2016

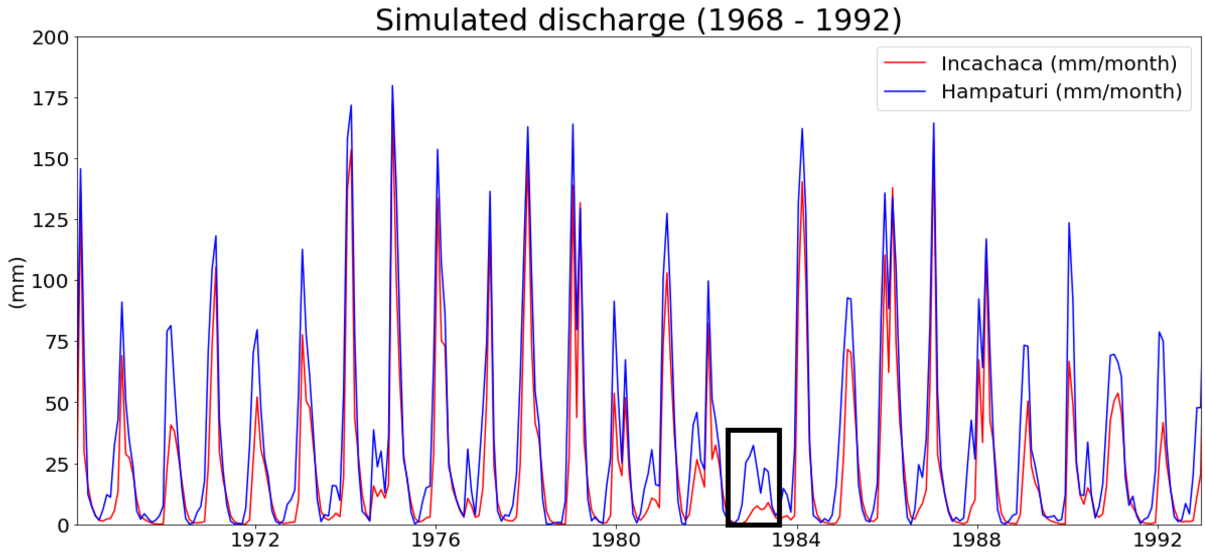

Figure 44: Simulated discharge of Incachaca and Hampaturi over the period 1968 - 1992

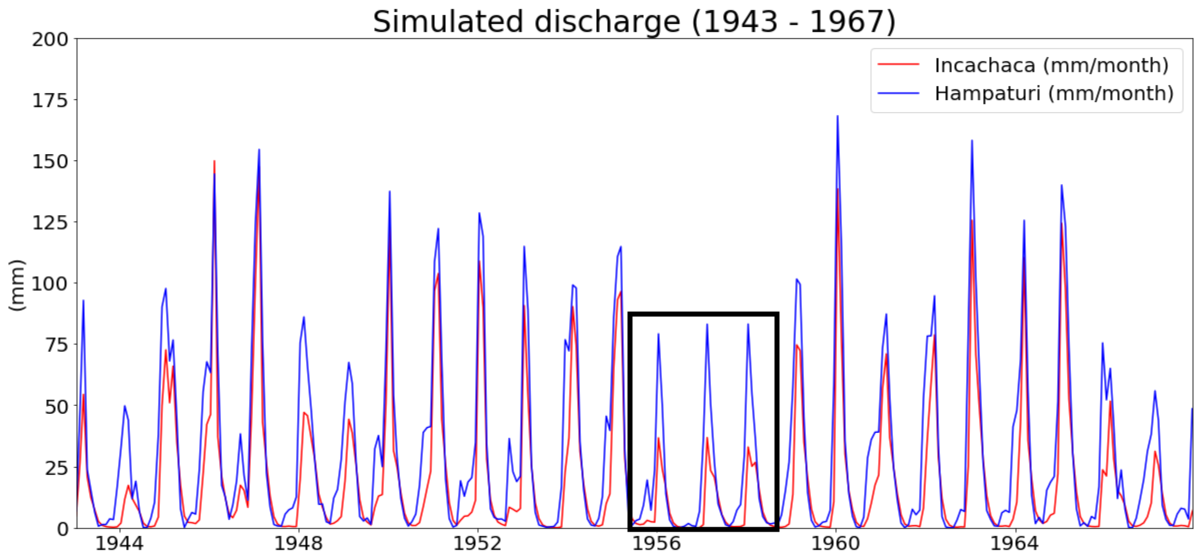

Figure 45: Simulated discharge of Incachaca and Hampaturi over the period 1943 - 1967